ESSAYS IN LABOR AND MACROECONOMICS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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May 2017

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Cornell University 2017

This dissertation contains three chapters that empirically examine the interactions among economic variables from three different fields: labor economics, macroeconomics, and financial markets. This dissertation lies at the intersection of these three fields, and the underlying theme is the empirical investigation that enhances our understanding of the mechanisms that drive economic activities that we observe today.

The first chapter examines how labor market composition and macroeconomic conditions affect each other. A dual labor market structure that consists of "permanent jobs" and "temporary jobs" is common in many Continental European countries and in Japan, and over the last two decades, the share of temporary workers in these countries has increased markedly. In this chapter, I demonstrate through an analysis of Japanese household panel survey data that permanent workers experience faster wage growth than temporary workers. Then, building a search and matching model of dual labor market with endogenous human capital accumulation, I show that, in the presence of two different types of jobs with different rates of return to experience, a slowing of the economic growth rate in a dual labor market structure can prompt a substantial shift in the composition of jobs.

The second chapter proposes a nonparametric method for studying the time series properties of macroeconomic variables. In particular, I focus on a class of learning networks called the Radial Basis Function (RBF). The main advantage

of the RBF method is its flexibility and that it requires minimal functional-form assumptions. To assess the potential value of the RBF method, I simulate data points using a nonlinear New-Keynesian (NK) DSGE model and show that the RBF time series can uncover the nonlinear NK structure from simulated data observations whose length is as small as 300 (quarters). I then compare the out-of-sample prediction performance of the resulting network formula with other traditional time series methods, i.e., Vector-Autoregression and Bayesian VAR models. Finally, I apply this RBF time series method to US macroeconomic data from 1960-2010.

The third chapter studies the link between the probability of default implied by Credit Default Swaps (CDS) spreads and the final prices of the defaulted bonds as established at the CDS settlement auctions. We observe that the post-default recovery rates at the observed spreads imply markets were often 'surprised" by the credit event. We find that the prices of the bonds that are deliverable at the auctions imply probabilities of default that are systematically different than the default probabilities estimated prior to the event of default using standard methodologies. We discuss the implications for CDS pricing models. We analyze the discrepancy between the actual and theoretical CDS spreads and we find it is significantly associated both to the CDS market microstructure at the time of the settlement auction and to the general macroeconomic background. We discuss the potential for strategic bidding behavior at the CDS settlement auctions.

BIOGRAPHICAL SKETCH

Nobuyuki Kanazawa was born in Tokyo, Japan. He graduated from Soka University of America in 2009 with a Bachelor of Arts in Liberal Arts. Nobuyuki continued his education at New York University where he earned a M.A. in Economics in 2011. In August 2011, he began his graduate studies in the Department of Economics at Cornell University.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my committee chair, Professor Karel Mertens. His constant encouragement and insightful advice were crucial not only for completing this dissertation but also for helping me gain intellectual knowledge and understanding of the art of economic research. I would also like to thank my other committee members, Professor Levon Barseghyan and Professor Christopher Huckfeldt for they were always willing to discuss my problems and offer words of encouragement. I have also benefited greatly from the discussion I had with faculty members and students at the macro lunch group at Cornell.

Throughout the long journey of my education, my undergraduate advisor, Edward Feasel, has always supported me and encouraged me. I would like to also thank Luisa Zanforlin, who is the co-author of the third chapter. I have benefited greatly from our many discussions.

I would also like to thank my friends who have supported me during my time at Cornell. In particular, I would like to thank Susan Abraham, Sueli Mori, Itaraju Brum, Arjan Singh, Ritwick Ghosh, Takaaki Masaki, Ippei Shibata, Daisuke Fujii, Boyang Zhang, and Duc Truong.

Finally, I would like to thank my family: my parents, Toshio and Yuriko, my siblings, Mitsuo and Toshiko, and my wife, Hitomi. Their warm and unwavering support is what assisted me to get where I am today.

The data for this analysis, the Japan Household Panel Survey (JHPS/KHPS) was provided by the Panel Data Research Center at Keio University.

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CHAPTER 1

GROWTH AND LABOR MARKET COMPOSITION

1.1 Introduction

This paper studies the effect of the rate of economic growth on the composition of the labor market when that market consists of two types of employment, which are referred to as "permanent employment" and "temporary employment."[1] In many Continental European countries and in Japan, the share of temporary workers among all employees has increased markedly over the last two decades. This trend is commonly attributed to changes in labor market regulations that enforce stronger job protection or legislative decisions that facilitate the creation of temporary jobs.[2] While these legislative factors play some important role, this paper argues that, under a certain condition, a slowdown of economic growth alone can create a considerable increase in the share of temporary workers without any changes in legislation. The key mechanism hinges on the difference in the rate of wage growth between permanent jobs and temporary jobs. In particular, when the rate of wage growth is greater for permanent jobs than for temporary jobs and, at the same time, the economy grows at a slower rate, the value of future wage growth is discounted at a higher rate. This results in holding jobs that promises fast wage growth (permanent jobs) less valuable today, leading workers to choose temporary jobs rather than permanent ones.

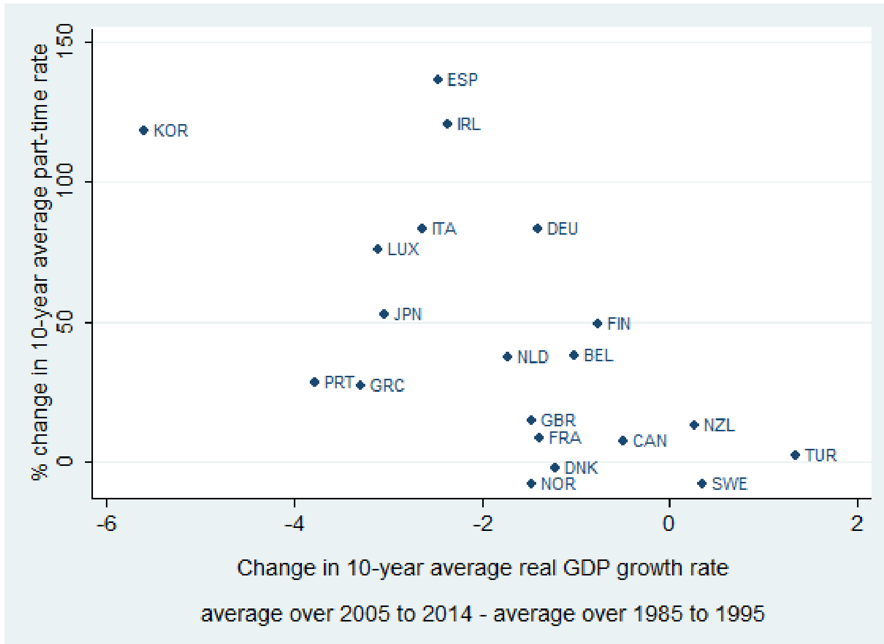
Simple exercise of comparing the changes in real GDP growth rates and the

[1] How these types of employment are referenced in the literature varies. Examples include "Good jobs" versus "Bad jobs", "Standard jobs" versus "Non-standard jobs", and "Regular employment" versus "Fixed-term employment".

[2] See [17] and [13].

Figure 1.1: Part-time employment rate and real GDP growth rate

Changes in 10-year average part-time employment rate and changes in 10-year average GDP growth rate: average over 1985-1994 versus average over 2005-2014



Source for part-time employment rate: OECD data, Source for real GDP: OECD Statistics

Notes: due to data availability, averages are over 1) 1986-1995 for New Zealand and Portugal; 2) over 1987-1995 for Netherlands; 3) over 1988-1995 for Turkey; and 4) over 1989-1994 for Finland, South Korea, and Norway.

changes in part-time employment rates for OECD counties reveals the primitive relationship between the GDP growth rates and the part-time employment rates.[3] Figure 1.1 plots the percentage change in the 10-year average of the part-time employment rate between 1985-1994 average and 2005-2014 average on the vertical axis.[4][5] The horizontal axis of Figure 1.1 shows the change in the 10-year average of annual GDP growth rates between 1985-1994 average and

[3]United States is excluded from Figure 1.1 because part-time employment rate is not available for the US in OECD data.

[4]Part-time employment is defined by OECD data as follows "part-time employment is ... people in employment (including both employees and self-employed) who usually work less than 30 hours per week in their main job. Employed people are those aged 15 and over who report that they have worked in gainful employment for at least one hour in the previous week or who had a job but were absent from work during the reference week while having a formal job attachment.

[5]% change in part-time rate = ((average part-time rate between 2005 and 2014) - (average part-time rate between 1985 and 1994))/(average part-time rate between 1985 and 1994) $\times 100$.

2005-2014 average.[6] Even though this analysis is primitive, Figure 1.1 clearly exhibits a negative relationship between the change in part-time employment rate and change in real GDP growth rate, suggesting that as the GDP growth slows down, the share of part-time workers tends to increase. Part-time workers in Figure 1.1 is simply defined as workers who work less than 30 hours a week, and the definition of temporary workers that I use in the remainder of the paper considers more characteristics of jobs including opportunities for promotion and rates of wage growth. However, the negative relationship exhibited in Figure 1.1 hints at the negative relationship between the share of temporary workers and the long-run growth rate of an economy. The goal of this paper is to offer an explanation for this negative relationship.

This paper focuses on Japan because: (i) the country experienced both periods of fast growth before 1990 and slow growth after 1990; (ii) the presence of two distinctively different types of jobs is well documented[7]; and (iii) during the slow growth period of the last two decades, the share of temporary employment has nearly doubled from 20% to 40%. Figure 1.2 shows four key Japanese economic statistics between 1980 and 2015. First, Japan experienced periods of both high growth prior to 1990 and low growth post-1990. The slow growth period after 1990 is sometimes referred to as the lost decades. The difference between the two periods is evident in the first panel (1.2a). The dotted lines indicate the average Japanese real GDP growth prior to and post 1990, which are 4.47% and 0.90%, respectively.

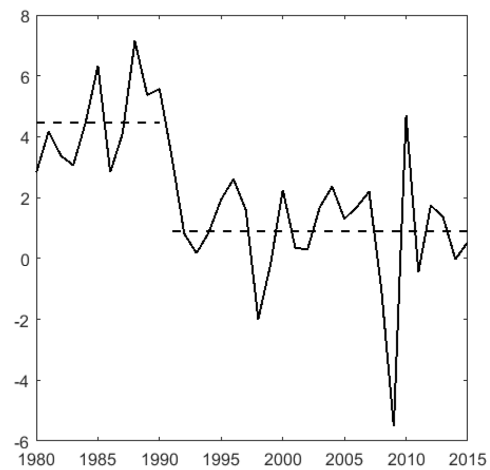
During the period of slow growth, the share of temporary workers among

[6] Change in real GDP growth rate = (average real GDP growth rate between 2005 and 2014) - (average real GDP growth rate between 1985 and 1994).

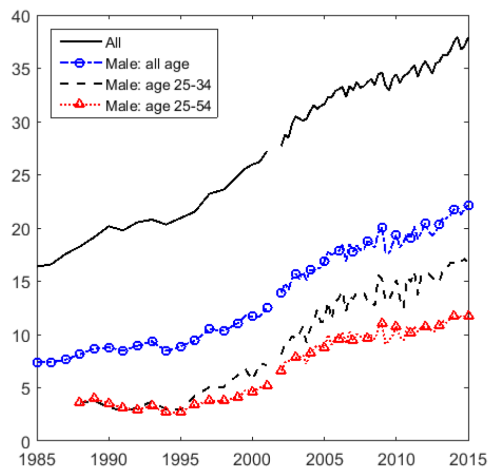
[7] Precise definitions of "permanent jobs" and "temporary jobs" are given in Section 1.3.

Figure 1.2: Japanese Economy

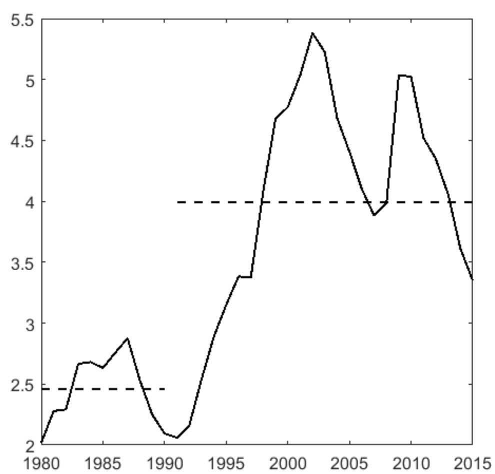
(a) Real GDP (percent change)



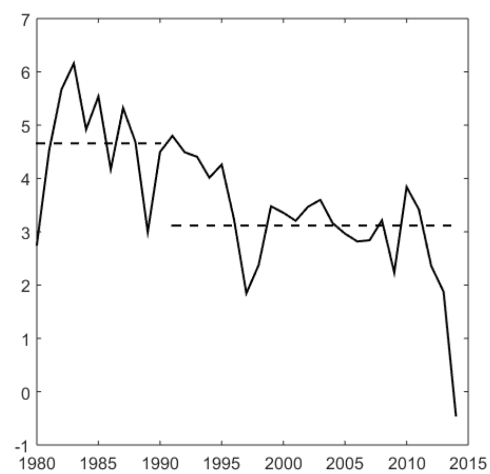
(b) Proportion of Temporary Workers (percent)



(c) Unemployment Rate (percent)



(d) Real Interest Rates (short-term)



Source for 1.2a: SNA (National Cabinet of Japan)
Source for 1.2b: ”The Special Survey of the Labour Force Survey” from 1984 to 2001, ”Labour Force Survey (Detailed Tabulation)” since 2002
Source for 1.2c: Labor Force Survey
Source for 1.2d: World Bank database

all employees doubled from 20% to close to 40%, as illustrated in panel 1.2b.[8] The share of temporary workers increases even when the sample is restricted to male employees and male employees of working age. This outcome implies that the increasing trend is likely to persist even after factors such as greater participation of female workers and aging demographics are removed. Interestingly, the most drastic change is observed for male workers between the ages of 25 and 34. The increasing trend in the share of temporary workers became a significant concern for the Japanese public when it was reported that temporary workers earn less wages, receive less generous benefits, expect very low rate of wage growth, and experience weaker job security than permanent workers do.

Panels (1.2c) and (1.2d) show the unemployment rate and real interest rate for Japan from 1980 to 2015. The unemployment rate increased from an average 2.46% before 1990 to an average 3.99% after 1990. The slow growth period appears to be associated with higher rate of unemployment. The average real interest rate decreased from 4.45% between 1980 and 1990 to about 3% after 1990. The reduction in the real interest rate means that the future incomes are discounted at a lower rate, which works against effect of the slow growth on the labor market. The combined effect of slower growth rate and lower real interest rates is thus ambiguous. To evaluate the impact of both effects, I propose a search and matching model that quantify these opposite forces.

Motivated by the observations described above, I build a search and matching model of a dual labor market that is populated by heterogeneous workers whose skills evolve endogenously according to their employment status. The model incorporates a dual labor market that is designed to capture two distinc-

[8]Data are retrieved from the Labor Force Survey, whose survey design is similar to that of the Current Population Survey in the U.S. Survey was redesigned in 2001. An overall increasing trend in the share of temporary workers is evident across the entire population.

tive labor markets for permanent jobs and temporary jobs. Workers are born as initially unemployed and with randomly assigned skills. Depending on their skill levels, they decide to search either in the permanent labor market or in the temporary labor market. In choosing which market to search for, unemployed workers face the following trade-off. If the unemployed workers search in the permanent market, they have a chance of finding jobs that enable them to fully utilize their own skills and that ensure greater job-security and on-the-job training. However, the probability of finding such jobs is low. In contrast, if the unemployed workers search in the temporary market, they have a higher probability of finding jobs. However, workers holding these jobs cannot utilize their own skills; instead they employ a technology that is common to all temporary jobs. In addition, the temporary jobs provide weaker job-security and less on-the-job training than the permanent jobs do. Given the parameter values that I estimate in Section 1.6, low skilled workers find it optimal to search for temporary jobs while high skilled workers search for permanent jobs; the observation that is consistent with the data.[9] Thus, in my model the existence of temporary jobs is motivated by the difference in workers' skill levels.

Given this trade-off between permanent jobs and temporary jobs, I pose the following question: How does low growth affect labor market composition? Suppose that an economy enters a slow growth steady state. Slower growth means that future income is discounted at a higher rate. This reduces the continuation value of a job because the cost of setting up the initial employment relationship is paid now; in contrast, the benefit of the employment relationship accrues in the future.[10] However, when the workers' skills are allowed to increase on the job and wages are negotiated during each period, the value

[9]See Section 1.3.3.

[10]This effect is often called the "capitalization effect," which is highlighted by [3] and [60].

of permanent jobs decreases at a much faster rate than the rate at which the value of temporary jobs decreases. The value of a permanent job is disproportionately affected because the permanent workers receive on-the-job training and have a higher probability of wage growth. In a slow growth economy, the present value of future wage growth goes down because the discount rate is higher. Faced with the low job-finding probability and the decreasing benefit of permanent jobs, some workers who would search for permanent jobs in a fast growth economy will, in a slow growth economy, search for temporary jobs. Thus, the share of temporary workers increases in the slow growth economy. The extent to which the share of temporary workers increases depends on the rate of skill accumulation for the permanent workers. In fact, when human capital accumulation is not allowed, slower economic growth has no impact on the composition of the labor market.

When estimated with the Japanese labor market dataset, my model attributes as much as 64.3% of the observed increase in the share of temporary workers in Japan to its slow growth. I also investigate how firing costs affect the composition of jobs. I find that reducing the cost of firing permanent workers results in a decrease in the share of temporary workers and a low unemployment rate.

The remainder of the paper is organized as follows. Section 1.2 reviews the relevant literature. Section 1.3 provides background information about the Japanese labor market and it defines "permanent jobs" and "temporary jobs" in the context of the Japanese labor market. Section 1.4 illustrates the mechanism using a simple model. Section 1.5 describes the full model. Section 1.6 lays out the calibration strategy, Section 1.7 shows the result, and Section 1.8 concludes.

1.2 Related Literature

This paper contributes to the literature on growth and unemployment. A number of papers have studied the effect of growth on unemployment in a search and matching framework ([3], [60], [61]). One of the most heated debates has centered on the degree to which the new workers embody new technology. If all the technological progress is embodied by new workers, then growth and unemployment are positively correlated. In contrast, if technological growth is disembodied, meaning that both new and existing workers embody technological progress, then growth and unemployment will be negatively correlated. To address this issue, [61] evaluate a model that features embodied and disembodied technology, capitalization, and creative destruction effects. They conclude that embodied technology and creative destruction do not play a significant role in explaining the steady-state unemployment rate. Following their argument, this paper uses a search and matching model with disembodied technological progress.

The use of temporary workers in Japan has gained attention in recent years. [7] empirically examined factors that are most responsible for the rise of temporary employment in Japan. They found that changes in labor force and industrial composition account for only a quarter of the increase in temporary workers and that the decline of the importance of long-term employment helps to explain this trend. In a structural estimation of the career choices of young workers, [26] focus on young workers who began their careers as temporary workers. They conclude that in Japan starting a career as a temporary worker has a lasting effect on the welfare of young workers.

The paper builds on the framework of [34], who proposes a search model where the allocation of workers across different labor markets is endogenously determined. He then studies how this allocation changes over the business cycle. In contrast, I study how the allocation of workers across distinct jobs changes across growth regimes. In doing so, I identify a separate mechanism by which the impact of changes in growth rates on the allocation of workers depends on the difference in the rates of wage growth across permanent and temporary jobs. This paper is also related to research undertaken by [1], who developed a search and matching model in which high-wage (good jobs) and low-wage (bad jobs) jobs can coexist. Observing the increasing share of temporary employment in Continental European countries, [5] investigated the role of increased temporary employment in a general equilibrium search and matching model. He concluded that temporary jobs increase unemployment, reduce output, and raise productivity. [16] studied the relationship between financial constraints and the labor market composition of permanent and temporary jobs. They found that when firms are likely to be financially constrained, they choose to hire more temporary workers. Examining the experience of labor market reform in France, [11] discuss the effect of allowing firms to hire workers on fixed-term contracts. They conclude that the main effect of policy reform is a high turnover in entry-level jobs, which leads to higher unemployment.

In the area of the growth and the composition of jobs in the economy, this paper is most closely related to [53] and [72]. In a search and matching framework, [72] claims that through the capitalization effect, the share of temporary workers increases during times of low technological growth. [53] builds a search and matching model to quantify the strength of the capitalization effect in Japan. Although our papers are similar, his mechanism crucially depends on the substitutability between goods produced by permanent workers and goods produced by temporary workers. As the rate of substitution between permanent goods and temporary goods decreases, the effects of a change in trend growth on the composition of jobs also decreases. Given how difficult it is to measure the rate of substitution between permanent goods and temporary goods in the real world, I propose an alternative mechanism that relies on the difference in the rate of wage growth between the two types of employment by integrating heterogeneous workers' skills that evolve dynamically. Taking skill accumulation into account, I find that the effect of the rate of growth on labor market composition changes dramatically.

This paper is also related to a line of research that studies the effect of layoff regulations. On the theoretical side, [47] summarizes the literature by stating that the effects of layoff regulations on employment vary greatly depending on the assumptions of models. Early general equilibrium analyses by [15], [32] and [65] display a negative effect of lay-off costs on employment, while later general equilibrium models by [6] and [55] display positive employment effects of lay-off costs. In search and matching models that employ the standard assumption of a constant relative split in the match surplus between firms and workers, layoff costs tend to increase employment by reducing labor reallocation; in contrast, because of diminished private returns to work, employment effects tend to be negative in models that feature employment lotteries. In addition, empirical work (e.g. [36]; [10]; [4]) are inconclusive about the effect of layoff regulation. Focusing on the impact of layoff regulation on job composition rather than the level of employment, [17] build a model that explains the choice between permanent and temporary jobs. They argue that job protection law causes a large substitution of temporary jobs for permanent jobs. My paper also predicts that a stronger job protection increases the share of temporary workers. The difference between my paper and theirs lies at how in each model the existence of temporary jobs is motivated. [17] motivate the presence of temporary jobs by assuming that jobs are different in their expected life-span of productivity (some jobs are expected to become unproductive within months (i.e. seasonal jobs) while other jobs are expected to be productive for years). In contrast, I motivate the presence of temporary jobs on the basis of the difference in workers' skills.

1.3 "Permanent Job" and "Temporary Job" in the Japanese Labor Market

This section outlines the institutional background of the Japanese labor market, whose composition is the focus of this paper. In particular, I describe standard Japanese labor market practices that many believe differ from US practices, and I define "permanent employment" and "temporary employment" in the context of Japanese labor market practices. [41] summarize as follows a set of standard practices that are coherently observed in Japanese labor market:

1. Strong employment protection against lay-offs, which leads to a long job tenure.
2. Employee involvement in problem solving activities from the bottom-up, which encourages workers to exert discretionary effort and gain local knowledge.
3. Careful screening and extensive on-the-job training that increases worker

ability[11]

The workers who are covered by these standard practices I call "permanent workers." Another group of Japanese workers has an employment relationship that does not conform to these practices. They constitute the secondary segment of the Japanese labor market, and I refer to their situation as "temporary employment." These workers often are paid lower wages, receive less generous benefits, enjoy less control over their work, and have weaker employment protection than permanent workers ([41]). In this regard, the permanent and temporary jobs of the Japanese labor market are similar to the "good jobs" and "bad jobs" that are described in the good job and bad job literature and "permanent jobs" and "temporary jobs" in the literature that study European labor markets [12].

I define "temporary employees" as workers who fall into one of the following categories: (i) part-time worker, (ii) dispatched workers, (iii) contract workers, (iv) commission staff, or (v) other types of workers who are not permanent employees. This method of classification is consistent with the use of the term in the Labor Force Survey [13]. Under this system of classification some temporary workers work for more than 40 hours a week and some permanent workers can work less than 40 hours a week.

In the following sub-sections, I document three empirical facts about permanent and temporary workers: (i) the rate of wage growth is higher for per-

[11] [41] also highlighted the fact that other Japanese employment practices are distinguished by two additional variables: (4) A robust scheme to share information through unions so that information asymmetry between employees and between employees and management is avoided; and (5) Incentive schemes that include employee ownership of the firms and profit sharing, which encourage workers and the firm to develop a sense of shared interests.

[12] See, for example, [1] and [40]

[13] The survey design is similar to the U.S. Current Population Survey

manent workers, (ii) on average the job tenure of permanent workers is greater than that of temporary workers, and (iii) people with high school or middle school degrees are more likely to become temporary workers while people with college or higher degrees are more likely to become permanent workers.

The following empirical findings are based largely on two datasets: the Japanese Household Panel Survey (JHPS) and the Keio Household Panel Survey (KHPS). The KHPS is an annual panel household survey of 4000 households that was recorded each year from 2004 to 2014. The JHPS is another annual panel household survey of about 4000 households that was recorded each year from 2009 to 2014. I focus on the income of household heads aged 25 to 60 years who were recorded at least 4 times (waves). This criterion leaves us with about 2000 observations each year from 2004 to 2008 and about 3200 observations from 2009 to 2013. The classification of permanent worker and temporary worker follows the criterion described above.

1.3.1 Wage growth

First, I establish that there is a difference in the rate of wage growth between permanent workers and temporary workers. To identify the return on working at the same firm for additional year, I run a regression of log hourly wage on job tenure, job tenure squared, work experience, work experience squared, and their interaction terms with indicator for permanent workers. Additionally, the regression includes the following control variables: age, age squared, individual fixed effects, and fixed effects for year and industry. Let $\mathbb{1}_P$ be the indicator for permanent employment, then the regression can be specified as follows:

$$
\begin{aligned}
\text{wage}_{i,t} = & \alpha_0 + \alpha_1 \text{tenure} + \alpha_2 \text{tenure}^2 + \alpha_3 \text{work ex.} + \alpha_4 \text{work ex.}^2 \\
& \beta_0 \mathbb{1}_P + \beta_1 \text{tenure} \times \mathbb{1}_P + \beta_2 \text{tenure}^2 \times \mathbb{1}_P + \beta_3 \text{work ex.} \times \mathbb{1}_P + \beta_4 \text{work ex.}^2 \times \mathbb{1}_P \\
& + X_{i,t}\gamma + \epsilon_{i,t}
\end{aligned}
$$

Our parameters of interest are β_1, β_2, β_3, and β_4. If the wage growth rate is different across two types of employment, the β's should be jointly insignificant. The result is shown below in Table 1.1. First, the p-value of the F-test indicates that the null of joint insignificance of β's is rejected at 5% significance level, meaning that the annual rate of return for working at the same firm is different between permanent workers and temporary workers. For permanent workers with 5 years of job tenure and 10 years of work experience[14], for example, the annual return of staying at the current employer is 6.88%.[15] In contrast, the annual return of working at the current firm is 5.24% for temporary workers with the same years of job tenure and work experience. The difference in the rates of wage growth for this example is about 1.63%, and this difference is statistically significant. The result is consistent with common practices documented in Section 1.3 wherein permanent workers accumulate local knowledge within a firm and receive extensive on-the-job training; temporary workers, in contract, do not.

[14] Aprrox. 30 years old who switched job once

[15] After removing the effects of year, age, industry.

Table 1.1: Return on working

	Permanent	Temporary
Avg. years of job tenure	14.10 yrs	5.11 yrs
Avg. years of work exp.	21.40 yrs	14.94 yrs
Avg. years of job tenure for both types	12.81 yrs	
Avg. years of work exp. for both types	20.68 yrs	
Annual wage growth for workers with 5 yrs of tenure and 10 yrs of exp.	5.24%	6.88%
Difference in wage growth for workers with 5 yrs of tenure and 10 yrs of exp.	1.63%	
Annual wage growth for avg. workers with 12.8 yrs of tenure and 20.68 yrs of exp.	4.05%	5.14%
Difference in wage growth for avg. workers with 12.81 yrs of tenure and 20.68 yrs of exp.	1.08%	
Observations	9,524	
R^2	0.0754	
p-value for F-test ($\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$)	0.0154	

Data are from KHPS and JHPS, 2004-2014. For each year, the sample is restricted to workers who continued working at the same firm from the previous year.

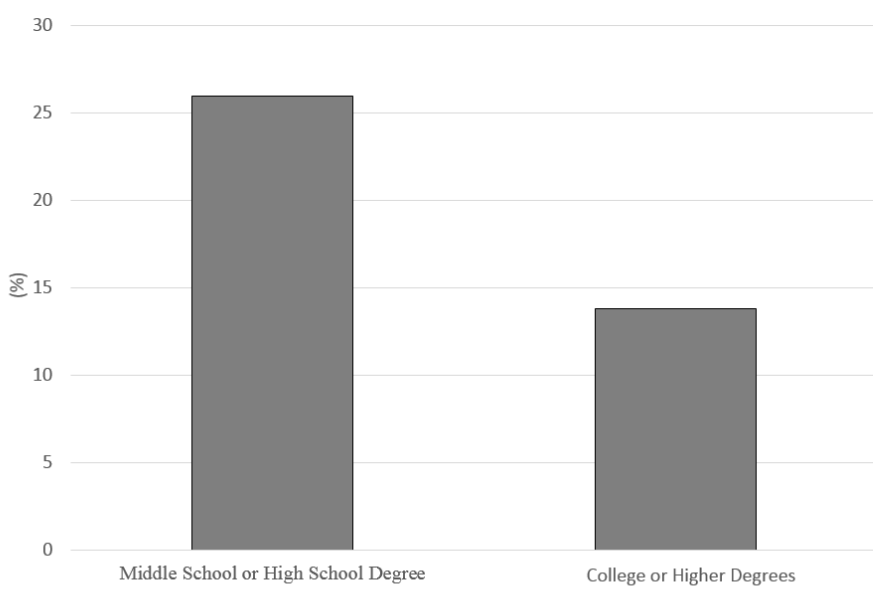
1.3.2 Job tenure

Next, I examine differences in the job tenure of permanent workers and temporary workers. The data are obtained from the JHPS and KHPS datasets. The data show that permanent workers stay with the same employers considerably longer than temporary workers. In 2006, the average length of stay with the same employer was 14.163 years (standard deviation is 11.169) for both types of workers. More specifically, the average length of the job tenure of permanent workers was 15.51 (standard deviation is 11.098) years, whereas for temporary workers it was 5.04 years (standard deviation 6.34). The test for the difference in the mean rejects the null that across the two types of workers the means are equal at the 1% significance level. In summary, permanent workers on average stay with the same employers about three times longer than temporary workers.

1.3.3 Educational attainment

The assumptions in my model induce low skilled workers to search for temporary jobs and high-skilled workers to search for permanent jobs; I present an observation that is consistent with this prediction. Since workers' innate productive capacities are difficult to measure, I use workers' educational attainment as a proxy for their skills. Figure 1.3 displays in the case of male employees the shares of temporary workers who have different levels of educational attainment. The share of temporary workers is highest among employees with middle or high school degrees (26% in 2012). In contrast, the share of temporary workers is lowest among employees who have college or higher degrees (12% in 2012). While this is not a perfect measure of workers' skills, it hints at the difference in the workers' traits across the two types of employment as measured by educational achievement.

Figure 1.3: Share of temporary workers by the level of education for men in 2012



Data from Employment Status Survey, 2012

Having documented these facts, I present my model in the following section.

1.4 Simple Model

For an illustration of a mechanism, I first build a simple model that features two types jobs. For convenience, I refer to the first type of job a permanent job and the second type of the job a temporary job. These two types of jobs are identical except that wages for permanent workers exhibit growth while wages for temporary workers remain fixed for their entire career. Workers employed in the permanent jobs initially receive wages, w_{perm}. In the next period, their wages increase to w'_{perm}, which will then be fixed for the rest of their careers. I further assume that once attached, the employed workers do not separate from the jobs.

Besides the wage growth that is specific to the permanent workers, the wages of both sectors will increases at the common rate of γ_X, which reflects the growth rate of the economy.

Let W_{perm} denote the present value of a permanent worker. Then,

$$W_{\text{perm}} = w_{\text{perm}} + \beta\gamma_X \frac{w'_{\text{perm}}}{1-\beta\gamma_X}, \tag{1.1}$$

where β is a discount factor.

Temporary workers do not experience wage growth. Thus, the value of a temporary worker is:

$$W_{\text{temp}} = \frac{w_{\text{temp}}}{1-\beta\gamma_X} \tag{1.2}$$

An unemployed worker is indifferent between searching for a permanent job and a temporary job if the following condition holds:

$$W_{\text{perm}} = W_{\text{temp}}$$

This condition requires the following wage structure: $w'_{\text{perm}} > w_{\text{temp}} > w_{\text{perm}}$

Suppose now that the technological growth that is common to both types of workers decreases, $\gamma_X \downarrow$. Then, values of both permanent workers and temporary workers decrease. For the unemployed workers to continue to be indifferent between choosing between permanent jobs and temporary jobs, the values of a permanent worker and that of a temporary worker must both go down at the same rate, $dW_{\text{perm}}/d\gamma_X = dW_{\text{temp}}/d\gamma_X$. On the contrary, the unemployed workers prefer temporary jobs if the value of permanent workers decreases at a greater rate than than the rate at which the value of temporary workers decreases: $dU_{\text{perm}}/d\gamma_X > dU_{\text{temp}}/d\gamma_X$.

It turns out that if the permanent jobs feature wage growth while the temporary jobs do not, then the rate of reduction in the value of permanent jobs is larger in response to the decrease in γ as follows:

$$\frac{dW_{\text{perm}}}{d\gamma_X} = \frac{\beta w'_{\text{perm}}}{(1-\beta\gamma_X)^2}\left((1-\beta\gamma_X)+\beta\gamma_X\right) > \frac{\beta w_{\text{temp}}}{(1-\beta\gamma_X)^2} = \frac{dW_{\text{temp}}}{d\gamma_X}$$

since $w'_{\text{perm}} > w_{\text{temp}}$.

Because changes in the discount factor affects only through wages in the future periods, the rate of response is larger for the permanent sector where future wage is higher than the temporary wages. Thus, the unemployed workers who were previously indifferent between permanent jobs and temporary jobs now prefer to be employed in temporary jobs when γ decreases. This simple model, however, does not take into account the general equilibrium effects of a slow growth. Specifically, when more people search for temporary jobs, the temporary labor market becomes tighter, which makes finding a temporary job more difficult and searching in the temporary labor market less attractive. Importantly, the simple model also ignore the effects through the wages. To fully evaluate the effects of a slow growth on the labor composition, I build a full model in the following sections.

1.5 Full Model

1.5.1 Environment

The model builds on [34] who incorporates elements of the Diamond-Mortensen-Pissarides search and matching model and the [48] model of human capital accumulation and depreciation

The economy is populated by risk-neutral workers and firms. Each employment relationship consists of a worker-firm pair. Workers are born unemployed and have skills that are drawn from a log-normal distribution: $\log(h) \sim N(0, \sigma_h^2)$. The skills of each worker dynamically evolve according to his or her employment status, as specified below.

Two labor markets comprise my model. The first is the permanent job market and the second is the temporary job market. These two employment types differ from one another in two respects: (i) while a firm must pay a firing cost to dissolve a permanent match, there is no cost of dissolving a temporary match; and (ii) permanent workers use their skills in the production process, in contrast to temporary workers, who do not utilize their skills. I assume that firing costs constitute waste rather than transfer to workers (i.e., administrative and legal costs).

Once an employment relationship is formed, firms produce goods according to the following linear technologies:

$$\tilde{y}_{\text{perm}} = \underbrace{X}_{\substack{\text{labor-augumenting} \\ \text{technology}}} \times \underbrace{h}_{\text{skill level}}, \qquad \tilde{y}_{\text{temp}} = \underbrace{X}_{\substack{\text{labor-augumenting} \\ \text{technology}}} \times \underbrace{A}_{\substack{\text{temporary} \\ \text{technology}}}$$

I assume that while permanent workers can make use of their skills, temporary workers use a technology that is commonly available to all temporary workers. The productivity of temporary workers is fixed at $\bar{A}$.[16]. To analyze the effect of growth, I assume that there is a labor-augmenting technology, X.[17] Additionally, I assume that all separations occur for exogenous reasons. The assumption of exogenous separation is not necessary for the effect of slow growth on job composition to be propagated.

That there is no on-the-job search reflects the fact that in Japan a direct transition from temporary employment to permanent employment is rare. [26], who conducted a structural estimation of the career choices of young workers in Japan, found that temporary employment is seldom a stepping stone to permanent employment. My assumption that there is no job-to-job transition is consistent with the observed extremely long job tenure documented in Section 1.3.2. Finally, I focus on stationary stochastic equilibrium.

[16]This productivity structure for temporary workers implies that temporary jobs are "skill-neutral".

[17]See Section 1.5.3 and A.2 for more detail

1.5.2 Labor Markets Construction

There are two labor markets. During each period, unemployed workers with skill level, h, choose in which market to search for a job. The search is random within the same market.

The match is formed according to a Cobb-Douglas function that takes job-seekers and vacancies as factors of input. Let M denote the number of matches and let u and v be the number of job-seekers and vacancies, respectively. The match is formed according to the following:

$$M_j = \overline{m}_j u_j v_j^{1-\psi} \quad \text{where } j \in \left\{\text{perm, temp}\right\}$$

, where $\overline{m}_j$ is a constant match efficiency. The match efficiency is different across two markets. For convenience, I define market tightness as the ratio of vacancies per job-seeker: $\theta_j = v_j/u_j$. Then, the job-finding probability can be defined as $f(\theta_\text{j}) = \bar{m}_\text{j}\theta_\text{j}^{1-\psi}$ and the job-filling probability as $q(\theta_\text{j}) = \bar{m}_\text{j}\theta_\text{j}^{-\psi}$ for $j \in \left\{\text{perm, temp}\right\}$.

The presence of the firing cost changes the value functions of the permanent workers and firms as well as the wage structure of the permanent workers. Following [55] and [63], I assume that firms that reject new permanent workers do not have to pay firing costs because their employment relationships have not yet started. Once they start working, the firms must pay firing costs when their matches are destroyed. This setting gives rise to a two-tier wage structure for permanent jobs, which is often described to as an "inside" wage and "outside" wage ([44]). I denote w^N_{perm} to be the wage for a newly employed permanent worker and w^E_{perm} to be the wage of an existing permanent worker. Because of the presence of the two-tier wage structure, there have to be two value functions for the permanent workers and jobs.

1.5.3 Balanced Growth

Following [60] and [61], my model assumes disembodied technological growth. I assume that there is a labor-augmenting technology, X_t that exhibits a steady state rate of growth as $\gamma_X = X_{t+1}/X_t$ for all t. Furthermore, I assume that all exogenous variables grow at the constant rate of γ_X. Thus, the cost of vacancy, κ_j, the unemployment income, b, and the firing cost, ϕ, for $j \in \{\text{perm}, \text{temp}\}$ all grow at the rate of γ_X. Under this assumption, the economy is on a balanced growth path. In the following sections, I present a model under which all variables are divided by X (i.e. $y_{\text{perm}} = \tilde{y}_{\text{perm}}/X$). For a detailed derivation, please refer to Section A.2.

1.5.4 Human skill dynamics

The workers in my model are endowed with skills. The set of skills are measured between $\underline{h}$ and $\overline{h}$, and each skill-level is located at Δ_h distance from the others. Human capital in my model evolves dynamically. Given that wages are negotiated each period, the wages grow as workers' skills upgrade while on-the-job. This is one way to capture the wage growth described in 1.3.1. According to [64], in the U.S. there are two main sources for an observed earnings/experience profile: (1) skill accumulation and (2) job search (including outside job offers). In my model, workers increase their wages only by accumulating more skills. My model ignores the wage growth from an on-the-job search because in Japan the job-to-job transition rate is small. As noted in Section 1.3.1, the rate of wage growth is different across the two types of employment. To capture the different rate of wage growth, I denote π_{perm} as the probability of a skill upgrade by Δ_H

for permanent workers and π_{temp} as the probability of a skill upgrade for temporary workers. Thus, during each period, π_j fraction of workers in sector j who have an h skill-level upgrade their skills to $h + \Delta_h$ during the next period.

In addition, unemployed workers face the probability of skill deterioration with the probability, π_{u}. Thus, for unemployed workers who have skill-level, h, their skills go down to $h - \Delta_h$ each period with the probability π_u.

1.5.5 Value of Unemployment

Let $U(h)$ denote the present value of an unemployed worker who has h skill-level.

$$U(h) = b + \beta(1-\nu)\gamma_X \max \mathbb{E}\left[U_{\text{perm}}(h'), U_{\text{temp}}(h')\right] \tag{1.3}$$

Unemployed workers first receive an unemployment income, b, and decide whether to search in the permanent market or the temporary market.

Let $U_{\text{perm}}(h)$ denote the present value of unemployed workers who seek employment in the permanent labor market, and let define $U_{\text{temp}}(h)$ as the present value of unemployed workers who search in the temporary market. Then,

$$U_{\text{perm}}(h) = f(\theta_{\text{perm}})(W^N_{\text{perm}}(h) - U(h)) + U(h), \tag{1.4}$$

$$U_{\text{temp}}(h) = f(\theta_{\text{temp}})(W_{\text{temp}}(h) - U(h)) + U(h), \tag{1.5}$$

where $\beta = 1/R$ is the discount factor, ν is the exogenous probability of retirement, and γ_X is the steady state rate of labor-augmenting technological growth.

Once the unemployed worker decides what market to search, the unemployed worker finds a job with the probability $f(\theta_{\text{j}})$ for $j \in \{\text{perm}, \text{temp}\}$. If the unemployed worker could not find a job, then she will remain unemployed when the next period starts.

For reasonable parameter values, all workers with a skill level above a given cutoff h^* choose to search in the permanent market because the value of searching in the permanent market exceeds the value of searching in the temporary market. Thus, for $h > h^*$, $U_{\text{perm}}(h) > U_{\text{temp}}(h)$. Similarly, all workers below cutoff h^* find it optimal to search in the temporary market. An unemployed worker who held a temporary job previously might find it optimal to search for a permanent job if, when he worked in the temporary job, he accumulated sufficient skills. In contrast, an unemployed worker who previously held a permanent job will search in the temporary market if his skill drops to a level below h^*.

1.5.6 Value of Worker

Let $W_{\text{perm}}(h)$ denote the present value of a permanent worker. Let $W^N_{\text{perm}}(h)$ denote the present value of a new permanent worker:

$$W^N_{\text{perm}}(h) = w^N_{\text{perm}}(h) + \beta(1-\nu)\gamma_X \, \mathbb{E}\left[(1-\delta_{\text{perm}})(W^E_{\text{perm}}(h') - U(h')) + U(h')\right], \quad (1.6)$$

subject to the law of motion for h.

An existing permanent worker faces an exogenous probability of match destruction, δ_{perm}, at the beginning of each period. If the match is not destroyed, then the worker stays at the same firm. The worker then provides labor and receives wages. Let $W^E_{\text{perm}}(h)$ denote the present value of an existing permanent worker:

$$W^E_{\text{perm}}(h) = w^E_{\text{perm}}(h) + \beta(1-\nu)\gamma_X \, \mathbb{E}\left[(1-\delta_{\text{perm}})(W^E_{\text{perm}}(h') - U(h')) + U(h')\right], \quad (1.7)$$

subject to the law of motion for h. The only difference between the value of a new worker and an existing worker is the wage.

Finally, let $W_{\text{temp}}(h)$ denote the present value of a temporary worker.

$$W_{\text{temp}}(h,z) = w_{\text{temp}}(h) + \beta(1-\nu)\gamma_X\,\mathbb{E}\Big[(1-\delta_{\text{temp}})(W_{\text{temp}}(h') - U(h')) + U(h')\Big], \tag{1.8}$$

subject to the law of motion for h.

1.5.7 Value of a Job

Let $J^N_{\text{perm}}(h)$ denote the present value of a new permanent job

$$\begin{aligned} J^N_{\text{perm}}(h) =& y_{\text{perm}} - w^N_{\text{perm}}(h) \\ &+ \beta(1-\nu)\gamma_X\,\mathbb{E}\Big[(1-\delta_{\text{perm}})(J^E_{\text{perm}}(h') - V) + V - \delta_{\text{perm}}\phi\Big], \end{aligned} \tag{1.9}$$

subject to the law of motion for h. The match continues to next period unless it is not exogenous with the probability δ_{perm}. If the match is destroyed at the beginning of next period, the firms pay the firing costs of ϕ.

Let $J^E_{\text{perm}}(h)$ denote the present value of an existing permanent job

$$\begin{aligned} J^E_{\text{perm}}(h) =& y_{\text{perm}} - w^E_{\text{perm}}(h) \\ &+ \beta(1-\nu)\gamma_X\,\mathbb{E}\Big[(1-\delta_{\text{perm}})(J^E_{\text{perm}}(h') - V) + V - \delta_{\text{perm}}\phi\Big], \end{aligned} \tag{1.10}$$

subject to the law of motion for h.

The value of an existing permanent job and the value of a new permanent job differ only in their wages. As explained above, wages differ because new permanent firms do not need to pay firing costs when they reject new workers.

Similarly, let $J_{\text{temp}}(h)$ define the present value of a temporary job:

$$\begin{aligned} J_{\text{temp}}(h) = & y_{\text{temp}} - w_{\text{temp}}(h) \\ & + \beta(1-\nu)\gamma_X \mathbb{E}\left[(1-\delta_{\text{temp}})(J_{\text{temp}}(h') - V) + V\right], \end{aligned} \tag{1.11}$$

subject to the law of motion for h. The value of temporary jobs is similar to that of permanent jobs except that temporary jobs do not incur firing costs.

1.5.8 Value of Vacancy and the Free Entry Condition

Finally, the value of posting a vacancy in the permanent market is

$$V_{\text{perm}} = -\kappa_{\text{perm}} + \beta(1-\nu)\gamma_X \mathbb{E}\left[q(\theta_{\text{perm}}) \int_h (J^N_{\text{perm}}(h) - V_{\text{perm}}) d\mu^h_{\text{perm}} + V_{\text{perm}}\right], \tag{1.12}$$

where μ^h_{perm} is the skill distribution of unemployed workers in the permanent market. I assume that at the time of posting vacancies, the firms do not know the skill distribution of the job-seekers. The worker's skill is revealed only after he or she and the firm meet. Thus, the job-filling rate is the same across all skill-levels. The cost of posting a vacancy is defined as κ_{perm} for permanent jobs. The worker and firm meet at a job-filling probability given by $q(\theta_{\text{perm}})$. If the vacancy meets a worker, then a new job is formed whose continuation value is given by $J^N_{\text{perm}}(h, z)$.

The value of posting a vacancy in the temporary market is

$$V_{\text{temp}} = -\kappa_{\text{temp}} + \beta(1-\nu)\gamma_X \mathbb{E}\left[q(\theta_{\text{temp}}) \int_h (J_{\text{temp}}(h) - V_{\text{temp}}) d\mu^h_{\text{temp}} + V_{\text{temp}}\right], \tag{1.13}$$

where μ^h_{temp} is the skill distribution of unemployed workers in the temporary market and κ_{temp} is the cost of posting a vacancy in the temporary market. Each vacancy meets the job-seeker with the probability of $q(\theta_{\text{temp}})$. In equilibrium, the free-entry condition drives the value of a vacancy in both markets down to zero: $V_{\text{perm}} = 0$ and $V_{\text{temp}} = 0$.

1.5.9 Wage Determination

Following [60], I assume that workers and firms negotiate wages such that they split the matching surplus according to the Nash Bargaining game. Following [63] and [60], I assume that there is a two-tier wage structure for permanent jobs. This assumption is motivated by the observation that newly employed permanent firms do not have to pay firing costs if they reject workers before the employment relationships begin. Once workers start working, firms have to pay their firing costs if they are laid off. Let η denote a worker's fixed bargaining power. According to the Nash Bargaining solution, the new permanent worker and the firm split the match surplus as follows:

$$(1-\eta)(W^N_{\text{perm}}(h) - U_{\text{perm}}(h)) = \eta J^N_{\text{perm}}(h) \tag{1.14}$$

The existing permanent worker and a firm split the match surplus as follows:

$$(1-\eta)(W^E_{\text{perm}}(h) - U_{\text{perm}}(h)) = \eta(J^E_{\text{perm}}(h) + \phi) \tag{1.15}$$

Finally, for the temporary worker and firm, the match surplus is divided as follows:

$$(1-\eta)(W_{\text{temp}}(h) - U_{\text{temp}}(h)) = \eta J_{\text{temp}}(h) \tag{1.16}$$

Then, wages for new permanent workers can be shown as follows:[18]

$$\begin{aligned}
w^N_{\text{perm}} &= (1-\eta)b + \eta\left(y_{\text{perm}} - \beta(1-\nu)\gamma_X(1-\delta_{\text{perm}})\phi\right) \\
&\quad + (1-\eta)\beta(1-\nu)\gamma_X\left\{(\pi_{\text{perm}}-\pi_u)U(h) + \pi_u U(h-\Delta_h) - \pi_{\text{perm}}U(h+\Delta_h)\right\} \\
&\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(1-\pi_u)f(\theta_{\text{perm}})(W^N_{\text{perm}}(h)-U(h)) \\
&\qquad\qquad + \pi_u f(\theta_{\text{j}})(W^N_{\text{j}}(h-\Delta_h) - U(h-\Delta_h))\Big\}
\end{aligned} \tag{1.17}$$

The wage equation (1.17) looks complicated. However, the basic intuition of the Nash Bargaining solution holds in this wage equation. The wage is the weighted average of the workers' outside options and firm profits. A worker's outside option is the unemployment income, b, plus the expected value of finding another job if the worker becomes unemployed. Note that there is a possibility that the workers' skill will drop to a level below h^* during the next period that they become unemployed. If their skills drops to a level below h^*, they will search in the temporary market. Thus, j in the last line of equation 1.17 could be either "perm" or "temp," depending on the workers' skill level. Firms and workers also take into consideration the value of being unemployed in the case of a skill upgrade if the match does not dissolve and the value of being unemployed in the case of a skill deterioration if the match is destroyed, both of which is captured in the equation's second line (1.17). Additionally, new workers are willing to accept lower initial wage if they can start working at firms and become existing workers during the next period. In this case, the workers can use the firing costs as a credible threat against the firm to demand a higher wage.

[18]See Appendix A.4 for the derivation.

For existing permanent workers, the wages are given by:

$$
\begin{aligned}
w^E_{\text{perm}} &= (1-\eta)b + \eta(y_{\text{perm}} + (1-\eta\beta(1-\nu)\gamma_X(1-\delta_{\text{perm}}))\eta\phi) \\
&\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(\pi_{\text{perm}}-\pi_u)U(h) + \pi_u U(h-\Delta_h) - \pi_{\text{perm}}U(h+\Delta_h)\Big\} \\
&\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(1-\pi_u)f(\theta_{\text{perm}})(W^N_{\text{perm}}(h) - U(h)) \\
&\qquad\qquad + \pi_u f(\theta_{\text{j}})(W^N_{\text{j}}(h-\Delta_h) - U(h-\Delta_h))\Big\}
\end{aligned} \tag{1.18}
$$

Note that because existing permanent workers now know that their employers have to pay firing costs if the matches dissolve, the workers can demand higher wages. In our wage equation for the existing permanent worker, this appears in the form of $\eta\phi$ in the first line of equation (1.18), which gives the additional wage premium for the existing permanent worker.

For temporary workers, the wages are as follows:

$$
\begin{aligned}
w_{\text{temp}} &= (1-\eta)b + \eta(y_{\text{temp}}) \\
&\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(\pi_{\text{temp}}-\pi_u)U(h) + \pi_u U(h-\Delta_h) - \pi_{\text{temp}}U(h+\Delta_h)\Big\} \\
&\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(1-\pi_u)f(\theta_{\text{temp}})(W^N_{\text{temp}}(h) - U(h)) \\
&\qquad\qquad + \pi_u f(\theta_{\text{temp}})(W^N_{\text{temp}}(h-\Delta_h) - U(h-\Delta_h))\Big\}
\end{aligned} \tag{1.19}
$$

Since no firing cost is incurred for temporary jobs, ϕ does not enter the wage equation for temporary workers.

1.5.10 Dynamics of Distribution

Finally, the unemployment rate for each skill-level evolves as follows:

$$\begin{aligned} u'(h) =& (1-\pi_u)(1-f(\theta_j)) \cdot u(h) + \pi_u(1-f(\theta_j)) \cdot u(h+\Delta_h) \\ &+ (1-\pi_{\mathrm{j}})\delta_{\mathrm{j}} \cdot (1-u(h)) + \pi_{\mathrm{j}}\delta_{\mathrm{j}} \cdot (1-u(h-\Delta_h)), \end{aligned} \tag{1.20}$$

where j in equation 1.20 could be "perm" or "temp" depending on the skill level, h.

1.6 Calibration

The model is calibrated to match data at the monthly frequency. Table 1.2 summarizes the externally calibrated parameters.

Table 1.2: Externally calibrated parameters

Variable	Description	Value / Source
R	Interest Rate	$1.0465^{1/12}$, interest rate before 1990
β	Discount rate	$1/R$
δ_{perm}	Separation rate for perm workers	0.0030, [53]
δ_{perm}	Separation rate for temp workers	0.0061, [53]
γ_X	Technological growth rate	$1.045^{1/12}$, growth rate before 1990
θ_{perm}	Labor market tightness in perm sector	1.0, normalization
θ_{temp}	Labor market tightness in temp sector	2.24, [53]
ψ	Matching elasticity	0.6, [52]
η	Nash bargaining power for workers	0.6, see text
ν	Retirement probability	0.00208, see text
$\underline{h}$	min skill level	0
$\overline{h}$	max skill level	5
Δ_h	Human capital increment	0.0336, 150 equispaced grid
σ_h	std. of initial skill dist.	0.494, see text

I set the interest rate $R = 1.0465^{1/12}$, which was the average real interest rate between 1980 and 1990. For the discount factor, I simply take the inverse of R. I set the steady state rate of technological growth, $\gamma_X = 1.045^{1/12}$, which translates into an average annual growth rate of 4.5%, which, in fact was the Japanese average GDP growth rate between 1980 and 1990.

I assume that matching efficiency parameters, $\bar{m}_j$ are different across sectors and that the elasticity parameters, ψ also are the same. [43] estimated that the elasticity, ψ, for the Japanese labor market is 0.6. This value lies in the plausible range of 0.5-0.7 that [59] report. I set $\eta = 0.6$ according to the Hosios condition.

For the benchmark calibration, I target the average monthly job finding rate of 0.155 and the average monthly separation rate of 0.0035. These are the averages of corresponding data moments between 1980 and 1991 as reported by [52] and [43]. Following [53], I calculate that the ratio of the separation rate for permanent workers to temporary workers is 0.49, as indicated in the Survey on Employment Trends conducted by the Ministry of Health, Labor and Welfare. The job separation rates for permanent workers and temporary workers are chosen such that both the aggregate separation rate in the economy and the ratio of the separation rates between the two types of workers are matched. The Report on Employment Service conducted by the Ministry of Health, Labour and Welfare reports the job openings to application ratios of both permanent and temporary workers, which reflect labor market tightness. Based on the data and the estimates used by [53], I target the ratio of labor market tightness for temporary to permanent $\theta_{\text{temp}}/\theta_{\text{perm}} = 2.24$. I normalize $\theta_{\text{perm}} = 1$. Each worker has an average working life of 40 years, which implies $\nu = 0.00208$. The maximum and minimum values of human capital $\underline{h}$ and $\overline{h}$ are chosen so that large masses of the skilled workers do not accumulate at the endpoints of the skill distribution. I set $\Delta_h = 0.0336$, using a grid that has 150 equispaced points.

Workers in my model are born with an initial skill level. I assume that the initial skill is drawn from a log-Normal distribution $\sim lnN(0, \sigma_h^2)$, and I estimate σ_h by first running the following regression using the Japanese Household Panel Survey:

$$\log(\text{monthly income}_{i,t}) = \alpha + X_{i,t}\beta + \eta_i + \epsilon_{i,t} \tag{1.21}$$

where $X_{i,t}$ includes job-tenure (cubic function), work experience (cubic function), employment type (permanent, temporary), and fixed effects for city-size, year, and industry. Then, σ_h is the estimated permanent deviation of η_i in equation 1.21, which equals 0.494.

Table 1.4 lists the internally calibrated parameters. I estimate the following parameters by a simulated method of moments: ϕ, b, $\bar{m}_{\text{perm}}$, $\bar{m}_{\text{temp}}$, $\bar{A}$, π_{perm}, π_{temp}, and π_{u}. These parameters are estimated so that the model-produced moments match the data moments below. There are as many parameters as there are targeted moments. I begin by targeting the share of temporary workers to be 8.0%, which was the average share of temporary workers for Japanese men during the years 1985 to 1990. By focusing on the male population, I avoid the effects that arise when there is greater female participation in the labor force. Following [53], I calculate from the Survey on Employment Trends conducted by Ministry of Health, Labor and Welfare that the ratio of job-finding rate of permanent workers to that of temporary workers is 0.45 . I also target the wage distribution of the p90/p50 ratio to be 1.88, which, as estimated by [45], were the average Japanese p90/p50 ratios prior to 1990. Using the estimated difference in return to working at the same firm between permanent workers and temporary workers provided in Section 1.3.1, I target the average difference in return on working between the two types of jobs to be 0.622%.[19] Finally, estimating from the KHPS and the JHPS datasets, I target the average wage ratio between permanent workers and temporary workers to be 1.681. The list of data moments is displayed in Table 1.3.

Table 1.3: Targeted moments

Moment	Data (Target)	Model Output
Job finding rate	0.155	0.1520
Ratio of job finding rate: perm/temp	0.450	0.4496
Job separation rate	0.0035	0.0039
Unemployment income	0.5796 (40% of average wage)	0.5691
Share of temporary workers	0.080	0.0812
Wage distribution, p90/p50	1.880	1.7942
Average return on job tenure for perm workers	0.622%	0.628%
Average wage ratio: perm/temp	1.6808	1.7454

Table 1.4: Internally calibrated parameters

Variable	Description	Value
ϕ	Firing cost	9.3714
b	Unemployment income	0.5691
$\bar{m}_{\text{perm}}$	Matching efficiency in permanent sector	0.1417
$\bar{m}_{\text{temp}}$	Matching efficiency in temporary sector	0.2282
A	Productivity of temporary worker	0.8535
π_{perm}	Probability of skill upgrade for perm sector	0.0204
π_{temp}	Probability of skill upgrade for temp sector	0.0150
π_{u}	Probability of skill deterioration for unemployed	0.0184

[19]The common wage growth component observed in Section 1.3.1 is captured in γ_X. The only margin that matters in my model is the *difference* between the rate of wage growth between permanent workers and temporary workers.

The estimated values of the parameters are shown in Table 1.4. Since the average wage of a permanent worker in my model is 1.4787, the firing cost is estimated to be approximately equal to six months of wage compensation.[20] Following [26] and [53], I target the unemployment income to be about 40% of the average monthly wage of all workers, which is 0.5796. The estimated value of b is 0.5691. The estimated value of the matching efficiency in the permanent market and the temporary market implies that job finding rates in these sectors are 0.1417 and 0.3151, respectively. These numbers are targeted so that the job finding rate for the overall economy also matches the average monthly job-finding rate in Japan prior to 1990, which was approximately 0.155. The productivity of temporary workers is estimated to be 0.8535. Each month, the probabilities of skill upgrades for permanent jobs and temporary jobs are estimated to be 2.04% and 1.50%, respectively. If workers are unemployed, each month their skills deteriorate with the probability of 1.84%.

1.7 Results

To determine how slow growth affects the dual labor market, I now set the annual rate of technological growth to 1%. This is roughly equivalent to the Japanese's experience of economic growth during the lost decade(s). For the benchmark result, I also decrease the market interest rate so that it equals the average real interest in Japan between 1996 and 2014. Decreasing the real interest rate in my model is important because as the interest rate goes down, the

[20] [42] estimated that in France the termination of the contract of a permanent job is 16% of the annual wage for an individual layoff and 50% of the annual wage for a collective layoff. Given that about four out of six layoffs are individual layoffs, the average cost is 20% of the annual wage. [9] found that firing costs in Spain are about 20% higher than in France. [5] estimated the firing cost are 51% of annual wages.

future incomes are discounted at a lower rate, which reduces the effect of slow growth on the labor market. I fully take this into account when I conduct the experiment by decreasing the real interest rate to a level that we observe in the data. Table 1.5 summarizes the quantitative result.

Table 1.5: Moments comparison under two regimes

Technological growth rate	(1) $\gamma_X = 1.04^{1/12}$	(2) $\gamma_X = 1.01^{1/12}$
Job finding rate	0.1520	0.1543
Job separation rate	0.0032	0.0035
Share of temporary worker	0.0812	0.1623
Average wage ratio: perm/temporary	1.7454	1.8282
Unemployment rate	3.39%	3.49%
Annual rate of interest	1.040	1.0279
Market tightness in perm. sector	1.000	0.8713
Market tightness in temp. sector	2.240	1.9703
Job-finding rate in perm. sector	0.1417	0.1341
Job-finding rate in temp. sector	0.3151	0.2994

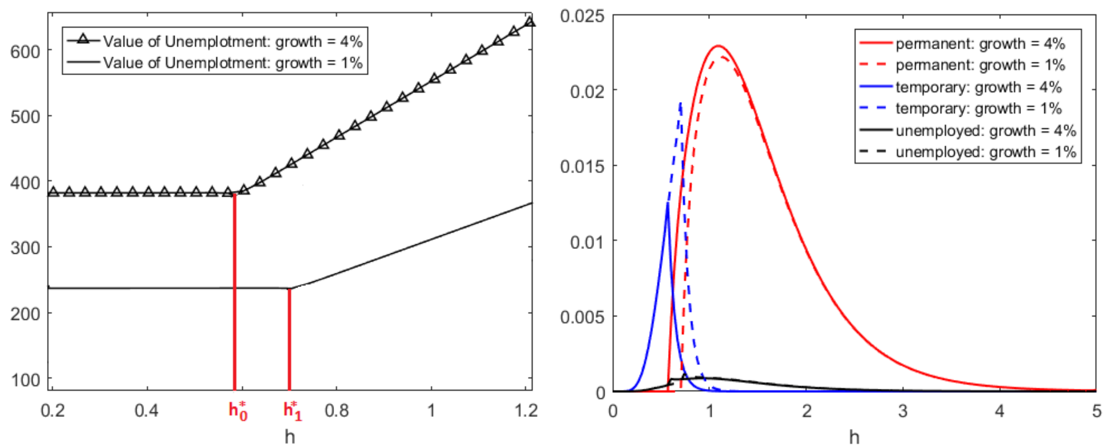
In Table 1.5, column (1) presents the model moments when the rate of technological progress is 4% annually; and column (2) displays the model moments when the annual rate of technological progress is 1%. The share of temporary workers almost doubled from 8.12% to 16.23%. The average share of temporary workers for men in Japan increased from 8.0% between 1985 and 1990 to 20.62% between 2010 and 2015. The model attributes as much as 64.3% of this increase to slow growth.

Figure 1.4a demonstrates the choices that unemployed workers face when deciding in which market to search for jobs. Figure 1.4a plots the values of unemployment for workers who have different skills for the 4% growth steady state and for the 1% growth steady state. The black line with triangles indicates the value of unemployment when the annual rate of economic growth is 4%. The red line that is extending from the point, h_0^*, shows the original cutoff level or skill. The unemployed workers whose skill level is below h_0^* optimally search for temporary jobs, whereas the unemployed workers whose skill level is above h_0^* search in the permanent market. The value of unemployment is flat when workers are searching for temporary jobs because regardless of the workers' ability, they face the same job-finding probability and use the same production technology once they are employed. In contrast, the value of unemployment increases with skill level when workers are searching for permanent jobs because they can fully utilize their skills at the time of production. The black solid line indicates the value of unemployment in the 1% growth steady state. As the rate of economic growth slows down, the value of unemployment goes down. In this steady state, the cutoff level, h_1^*, shifts to the right, which induces a larger fraction of workers to search in the temporary market. The cutoff level moves to the right because the decrease in the value of unemployment in the permanent market is more significant than the decrease of the value of unemployment in the temporary market. The reduction is larger for the permanent market because the present value of wage growth decreases as all future incomes are discounted at a higher rate. Considering this, the unemployed workers whose skill level is within the range of (h_0^*, h_1^*) will switch from searching for jobs in the permanent market to searching for jobs in the temporary market. Thus, the share of temporary workers in the economy increases.

The market tightness in both sectors decreased, which indicates that firms post fewer vacancies per job-seeker when the economy is in the slow growth steady state. The decrease in market tightness leads to a low job-finding rate. The job-finding rates in the permanent and temporary market decreased by

Figure 1.4: Baseline Calibration

(a) Value of Unemployment (b) Skill distribution by employment types



5.36% and by 4.98%, respectively. Reinforcing the points made in the previous paragraph, Figure 1.4b clearly demonstrates that in the slower growth steady-state, the left tail of the skill distribution for workers in the permanent market shifted to the right. As the average skill levels of the permanent labor market increases, the model also predicts that the wage ratio between permanent and temporary employment increases in the slow growth steady-state.

In reality, most permanent employment relationships begin during a period when workers, who are in their 20s or early 30s, have lower skills. Consistent with the model's prediction, Figure 1.2b shows that the most significant increase in the share of temporary workers was experienced by 25-34 year-old males: in this population the share of temporary workers increased from an average of 3.41% between 1988 and 1992 to an average of 15.56% between 2010 and 2014.

Somewhat counter-intuitively, for the economy as a whole, the job-finding rate in the slower growth steady state increased slightly to 0.1543; in the faster growth steady-state it was 0.1520. The job-finding rate increased because of the large increase in the share of temporary workers in the economy. The job-finding rate is higher for temporary employment, and, thus, increasing the share of temporary workers improves the matching efficiency for the labor market overall. Likewise, the separation rate increases for the economy as a whole because a larger fraction of workers are now employed in the temporary jobs whose the job separation rate is higher.

Finally, the unemployment rate of the aggregate economy will increase in the slow growth steady state. This is consistent with the Japanese experience, wherein the unemployment rate has increased significantly during the last two decades. In this model, unemployment goes down because a greater number of workers search in a temporary market whose matching efficiency is higher.

1.7.1 No Endogenous Skill Accumulation

To highlight the importance of endogenous skill accumulation in my model, I again lower the steady state growth rate in an economy from 4% to 1%, but I impose zero human capital accumulation (i.e. $\pi_{\text{perm}} = \pi_{\text{temp}} = \pi_{\text{u}} = 0$). In this environment workers are born with randomly realized skills, and these skills do not change for the rest of their careers. I re-calibrate the model to match the moments listed in Appendix A.5.

Table 1.6 summarizes the results of this experiment. The most striking result is that the share of temporary workers does not increase at all. Figure 1.5b shows that the change in the shape of the workers' skill distribution is very limited even after the steady-state growth rate has decreased to 1%. When human skills are not allowed to evolve, the rate of decrease in the value of searching in the

Table 1.6: No Human Capital Accumulation

Moments comparison under two regimes

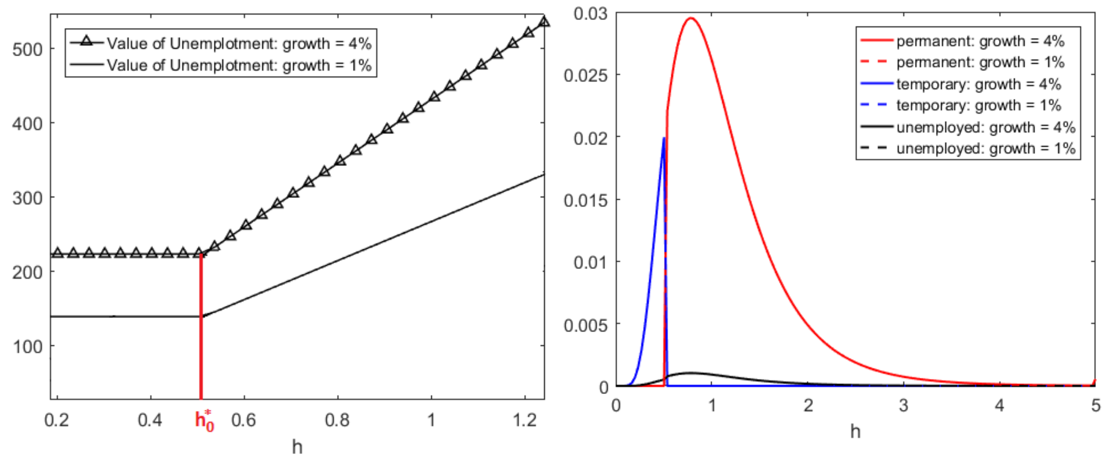
Technological growth rate	(1) $\gamma_X = 1.04^{1/12}$	(2) $\gamma_X = 1.01^{1/12}$
Job finding rate	0.1585	0.1580
Ratio of job finding rate: perm/temporary	0.4496	0.4493
Job separation rate	0.0033	0.0033
Share of temporary worker	0.0937	0.0937
Unemployment rate	3.28%	3.29%
Annual rate of interest	1.040	1.0279
Job-finding rate in permanent sector	0.1461	0.1456
Job-finding rate in temporary sector	0.3249	0.3240

permanent and of searching in the temporary sectors is symmetrical. As Figure 1.5a reveals, although the value of unemployment in the 4% growth steady state (black line with triangular) decreases when the economic growth becomes 1% (black solid line), the value of unemployment in the permanent market and the value of unemployment in the temporary market both go down by the same margin, which leaves the cutoff level h^* unaltered. In this case, workers will continue to compare the value of searching in the permanent market against the value of searching in the temporary market in the manner they did before the change occurred.

In this environment, the job-finding rate, the job separation rate, and the unemployment rate are not affected by the slowdown of economic growth as well. This section confirms that on-the-job training plays a key role in relationship between slow growth and labor market composition. The only source of wage growth in this model is skill accumulation. Thus, the steeper the rate of wage growth for permanent workers, the larger the impact on labor market composi-

Figure 1.5: No Human Capital Accumulation

(a) Value of Unemployment (b) Skill distribution by employment types



tion of changes in the growth rate.

1.7.2 Policy Experiment: Layoff Protection

Research indicates that strong protection against laying off permanent workers induces firms to hire more temporary workers than permanent workers.[21] The underlying intuition is that layoff protection increases the burden placed on employers when they hire permanent workers. In this section, I discuss whether the intuition holds in my model. Recently the Japanese government started a discussion about whether it should create clearer rules for laying off workers, including laws that require firms to pay lump-sum transfers to workers who are being fired. Such policies are said to produce effects that resemble those produced by the lenient layoff protection policy. Underlying the discussion is a question: do firms, which are inherently risk-averse, hesitate to lay off workers because the current layoff protection policies are vague? Many argue that loos-

[21] See [17].

ening layoff protection laws should promote a more invigorated flow within the labor market, which would help to alleviate occupational mismatches. I investigate this issue within my model's framework.

In this model, the parameter, ϕ, controls the difficulty of firing a permanent worker. Note that in my model ϕ is a pure waste that is not transferred to unemployed workers. In the experiment presented below, I compute the model statistics using different values of ϕ. Other parameter values are set according to the baseline calibration presented in Section 1.7. Throughout the experiment the steady-state annual growth rate is set to equal 1% and the annual real interest rate equals 2.79%. Note that in our baseline calibration, the estimated value of ϕ, 9.3714 is approximately equal to six months of the average wages of permanent workers. Table 1.7 summarizes the results of the model statistics.

Table 1.7: Model statistics with different layoff policies

	(1)	(2)	(3)	(4)	(5)
	$\phi = 0$	$\phi = 9.37/2$	$\phi = 9.37$	$\phi = 9.37 \times 2$	$\phi = 9.37 \times 4$
in terms of monthly wages	0 month	3 months	6 months	12 months	24 months
Job finding rate	0.1536	0.1518	0.1543	0.1551	0.1522
Ratio of job finding rate: perm/temp	0.4550	0.4550	0.4496	0.4372	0.4170
Job separation rate	0.0034	0.0034	0.0035	0.0036	0.0036
Share of temporary worker	0.1398	0.1398	0.1623	0.1860	0.2110
Average wage ratio perm/temp	1.7938	1.8004	1.8282	1.8638	1.9135
Unemployment rate	3.46%	3.50%	3.49%	3.52%	3.63%
Job-finding rate in perm. sector	0.1364	0.1347	0.1341	0.1317	0.1255
Job-finding rate in temp. sector	0.2968	0.2960	0.2994	0.3013	0.3011
Cutoff level, h^*	0.6711	0.6711	0.7047	0.7383	0.7718

Each column in Table 1.7 shows the model statistics; corresponding values of ϕ are at the top of the table. I first compare the results from column (1) and column (2) against the baseline result in column (3) where ϕ is approximately equal to 6 months of wages. Column (1) shows that when $\phi = 0$, the share of temporary workers is 13.98%. Compare this to 16.23%, which is the share of temporary workers in the baseline calibration in column (3). The share of temporary workers decreases because in this economy the job-finding rate for permanent jobs is high, which increases the value of searching jobs in the permanent market and induces more people to search permanent jobs. Accordingly, the cutoff level, h^* also decreases to 0.6711 (column (1)) from 0.7047 (column (3)) of the baseline calibration, which indicates that unemployed workers with a skill level between 0.6711 and 0.7047 find it optimal to search for temporary jobs rather than permanent jobs. The job-finding rate for permanent jobs is elevated because firms are posting more vacancies in the permanent market. Since the present value of permanent jobs increases as the firing cost goes down, firms will compete with each other to post more vacancies until the value of posting vacancies becomes zero. The separation rate for the overall economy also decreases because there is a decreased share of temporary workers, and so the unemployment rate goes down.

Columns (4) and (5) report model statistics when ϕ's are equal to as much as 12 months and 24 months, respectively, of average monthly wages. When ϕ equals 24 months of average monthly wages, the share of temporary workers goes up to a strikingly high level of 21.10% that is strikingly high compared to the baseline case of 16.23%. This is caused by the significant reduction in the job-finding rate in the permanent market, which is caused by the fact that firms now post fewer permanent market vacancies. As ϕ increases, the number of vacancy posting firms and the job-finding rate for permanent jobs decrease, which causes the value of searching in the permanent market to drop, too. Thus, the cutoff skill level when ϕ equals 12 months and 24 months of monthly wages increases to 0.7383 and 0.7718, respectively, which encourages workers who have skills below these new cutoff levels to search for jobs in the temporary market instead of the permanent market. In these economies, the job-finding rate in the permanent market is so low that workers who previously has searched in the permanent market now find it optimal to search in the temporary market. Finally, the job separation rate for overall economy goes up because the share of temporary workers increases, which results in unemployment rates that are higher than those found in the baseline model.

In summary, reducing firing cost decreases unemployment and the share of temporary workers. This conclusion is consistent with [17]'s finding that increasing the firing cost induces firms to substitute permanent workers for temporary workers. Loosening of layoff protection removes the burden placed on firms of hiring permanent workers and increases the value of permanent jobs, which motivate firms to post more vacancies in the permanent market. Thus, more job-seeker are attracted to the permanent market, and the share of temporary workers decreases.

1.8 Concluding Remarks

This paper investigates how the rate of economic growth affects the composition of the labor market. I build a search and matching model of a dual labor market that is inhabited by heterogeneous workers. I find that the rate of workers' skill accumulation on-the-job significantly affects the manner in which slow growth impacts labor market composition. Specifically, the higher the rate of skill accumulation for permanent workers, the greater the impact of slow growth on labor market composition. My model attributes as much as 64.3% of the observed increase in the share of Japan's temporary workers to that country's slow growth. Finally, I conduct policy experiments to determine how lay-off regulations change labor market conditions. When a faster rate of skill accumulation is combined with slower economic growth, the labor market condition can dramatically change.

CHAPTER 2

TIME SERIES ANALYSIS USING RADIAL BASIS FUNCTIONS: WITH APPLICATION TO THE US ECONOMY

2.1 Introduction

Understanding time series properties of macroeconomic variables has been a major focus of macroeconomic research. In this paper, I propose a neural-network based time series estimator using a learning network. In particular, I focus on a class of network called the Radial Basis Function (RBF). The neural-network time series approach is motivated by the limitation that the standard approach faces in identifying the dynamic effect of shocks because it relies on structural Vector-Autoregressions (VARs), which are linear. While VARs can be useful in answering macroeconomic questions that pertain to linear relationships between macroeconomic variables, questions such as the asymmetric effects of fiscal and monetary shocks cannot be answered within a VAR framework. In contrast, the network-based models have the following two advantages that mitigate the limitation that the parametric models face. First, network models are robust when encountering functional-form errors since they do not rely on restrictive parametric assumptions. Second, they are adaptive and respond to structural changes in the underlying data-generating process in ways that linear estimators cannot. With these two advantages, the neural-network base models are capable of answering questions about potential asymmetries in the economic structure without increasing the number of parameters to be estimated. In fact, the great degree of flexibility that the neural-network models permit is particularly attractive when researchers have little knowledge about the true functional form of the data-generating process. For example, after the recent financial crisis, the Federal Reserve set the federal fund rate to essentially zero and has kept it at the same level for more than 7 years. Many argued that the behavior of the economy is both quantitatively and qualitatively different when the interest rates is at the zero lower bound (ZLB). The flexibility that the network formulas can provide is beneficial in this context because it allows us to analyze the structure of the economy without relying on any restrictive parametric assumptions about the structure of the economy.

To validate the performance of our approach using a small sample size, I conduct a number of Monte-Carlo simulations, using a nonlinear New Keynesian model. Nonlinearity in this NK model comes from a kink in the central bank's monetary policy rule where the interest rates is restricted to be always positive. Using the simulated data, I compare the out-of-sample prediction error performance of the RBF estimator with the prediction error of traditional estimators, i.e., Vector-Autoregressions (VARs) and Bayesian VARs (BVARs). I find that the RBF estimator does equally as well as the VAR models and that the RBF estimator outperforms the BVAR models. Next, I conducted the impulse response analysis using the RBF estimator and compared the results with the impulse responses of the linear VARs. The gist of this exercise is testing if the RBF estimator can 'uncover' the structure of the nonlinear NK model without imposing any parametric assumptions. I found that the RBF time series analysis can successfully capture the quantitative difference in the responses of key macroeconomic variables between normal and ZLB periods in a manner that a linear VAR cannot. Even when the sample size is limited to as small as 300 periods (quarters), the impulse reposes of the RBF time series are able to capture the qualitative difference in how macroeconomic variables react to a shock to the discount factor between normal and ZLB periods.

I then applied the RBF estimator to the US quarterly data from 1955 to 2013. I found that the RBF estimator slightly underperforms in terms of 1 quarter- and 2 quarter-ahead predictions when it is compared with the VAR and BVAR models. However, the RBF estimator performs equally as well as the VAR and BVAR when it predicts 4, 8, and 12 quarters ahead. Finally, using the (utilization-adjusted) TFP, I examined the impulse responses of key macroeconomic variables in response to a positive TFP shock. I found that the RBF estimator can produce impulse responses that are different from the ones that are produced by conventional VAR models.

The rest of the paper is organized as follows: Section 2.3 reviews the related literature, including literature on the Radial Basis Function in Section 2.2. Section 2.4 describes the Monte Carlo simulation exercise, Section 2.5 illustrates empirical application of the RBF method to the U.S. data, and Section 2.6 concludes.

2.2 Radial Basis Function

In this paper, I focus on a particular class of learning network, which is the Radial Basis Functions. RBFs were first introduced as a solution technique for interpolation problems, and in the late 1980s, the RBF formulation was extended to perform more general task of approximation [1]. Consider some unknown function $y = f(x)$, which is to be approximated given a sparse dataset (x_t, y_t). In terms of multiple-regression analogy of the RBFs, the d-dimensional vector, x_t,

[1] see [14], [54], and [62]

may be considered the independent variables, while y_t the dependent variable. $f(\cdot)$ is the nonlinear function or the conditional expectation of y_t given x_t, hence:

$$y_t = f(x_t) + \epsilon_t, \quad E[\epsilon_t | x_t] = 0 \tag{2.1}$$

In the case of the Radial Basis Functions, $f(x_t)$ can be written as follows:

$$f(x_t) = \sum_{j=1}^{M} K_{\lambda_j}(\xi_j, x_t)\beta_j \tag{2.2}$$

$$= \sum_{j=1}^{M} D\left(\frac{\|x_t - \xi_j\|}{\lambda_j}\right)\beta_j \tag{2.3}$$

where each basis element is indexed by a location parameter or centroid, ξ_j, and a scale parameter λ_j. M is the number of centroids in the model. I choose the Gaussian density function for the kernel, D, since it is the most popular choice of the base for the RBFs. Roughly speaking, when a new input enters the system, the RBFs computes the Euclidean distance between the input and each of the centroids, ξ_j, for all j. Based on the distance measured, the RBFs compute the predicted value, $\widehat{y_t}$. I estimate the location parameters, ξ_j, scale parameters, λ_j, and the β's, to approximate the y_t by solving the following minimization problem:

$$\min_{\{\lambda_j, \xi_j, \beta_j\}_1^M} \sum_{t=1}^{T} \left(y_t - \beta_0 - \sum_{j=1}^{M} \beta_j \exp\left\{ -\frac{(x_t - \xi_j)'(x_t - \xi_j)}{\lambda_j^2} \right\} \right)^2 \tag{2.4}$$

Again, the RBF can be intuitively described as a real-valued function whose values depend only on the Euclidean distance between centroids and the inputs, weighted by scale parameters λ_j. The graphical description of the RBF is in Figure 2.1.

Finally, our RBF time series model is augmented with lags, denoted by p, which can now be written as follows:

$$y_t = \sum_{j=1}^{M} K_{\lambda_j}\left(\xi_j, \{y_{t-h}\}_{h=1}^{p}\right)\beta_j + \epsilon_t \tag{2.5}$$

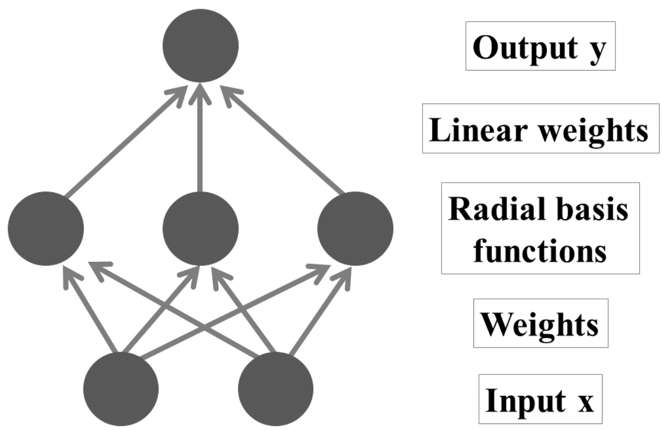


Figure 2.1: Graphical description of RBF

where ϵ_t, a vector of error terms.

2.2.1 Property of Radial Basis Functions

Although application of RBFs in economics is a relatively new development, some properties of this class of artificial neural networks have been studied in the last two decades in the field of computer science. First property of the RBF is its universal approximation property, which was introduced by [58], [73], and [28]. The main conclusion of these authors is that any continuous function on a compact domain can be approximated arbitrarily well by the RBFs.

Naturally, the next step of the universal approximation property is to consider how fast the approximation converges to the original function. To answer this question, [27] derived bounds on convergence of the RBFs given some assumptions about the smoothness of the functions being approximated. [56]

extended this result for the estimation problem and derived a bound on the "generalization error" of the RBFs, the error that an RBF network will make on unseen data. Their result is summarized in Figure 2.2. First, it is apparent that the generalization error is a decreasing function of the number of data points, N. Second, Figure 2.2 also shows that, given a number of data points, the error is, at first, a decreasing function of the number of network parameters, n, and after n exceed some threshold point, the error becomes an increasing function of n. Therefore, Figure 2.2 suggests that given a number of data points, there is a optimal number of parameter in the network formula that minimizes the generalization error. I will use the information criteria (IC) to determine the number of parameters in the RBFs.

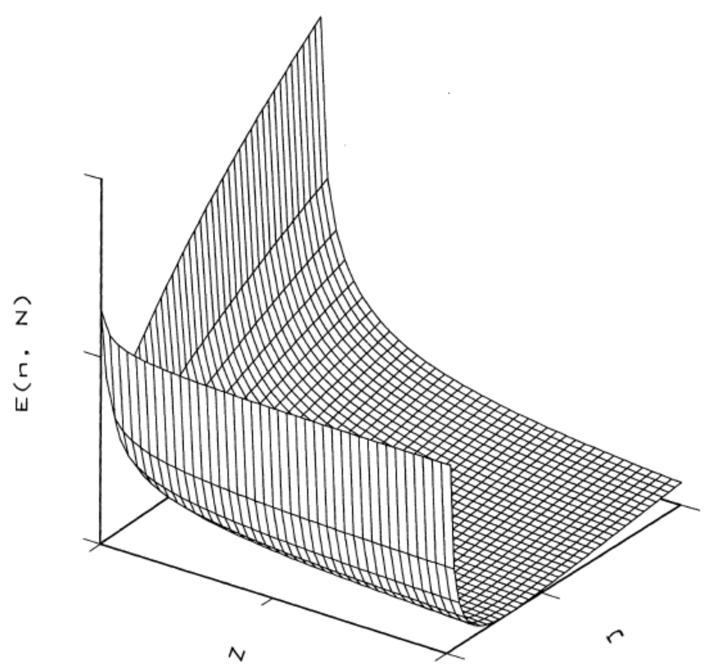


Figure 2.2: Generalization error E(n,N) for a Gaussian RBF as a function of number of data points N and the number of network parameters n (Reprinted from [56]).

[56] also found that the generalization error of unseen data depends on the number of observation and on the complexity of the network being approxi-

mated.

2.2.2 Parameter Estimation Methods

As specified in Section 2.2.1, there are three types of parameters that need to be estimated: centroids ξ_j, scale parameters λ_j, and β_j. In the neural network literature, estimating such parameters is called "training." Rate of convergence for RBFs is different depending on which training method is being used. This paper is not intended to answer which training method is optimal. Therefore, I employ one of the popular methods of training, which adopt the following procedure. First, I use a clustering method to fix the value of centroids, ξ_j. Some argue that the global solution method is ideal when estimating the centroids to minimize the equation (2.4), but such a method exponentially increases the computational costs. Rather, a common practice is using a K-clustering method to determine the value of centroids. In this paper, I use a clustering method proposed by [50] because it is shown to be pick data points that best represents the entire sample.

After I estimate the centroids, I then use global optimization algorithm ("interior-region" algorithm) to determine the scale parameters, λ_j. One convenient property of the RBFs is that after ξ_j and λ_j are pinned down, β_j can be estimated in a usual OLS manner, which greatly reduces the computational costs. Thus, I estimate the values of λ_j and β_j simultaneously in such a way that it will minimize the error specified in equation (2.4). Finally, I restrict number of parameters to be estimated such that it does not exceed the number of parameter used in the VAR model.

2.3 Literature Review

This paper is obviously related to the literature on nonlinear time series analysis. As described by [8], the literature can be mainly classified into two.

The first approach to capture nonlinearities relies on the use of regime-switching VAR models including threshold VARs (e.g., [33]) and Markov-switching VARs ([30]). One caveat of this approach is that, while regime-switching VARs can capture state dependence of macroeconomic variables, the relationships captured in each state have to be linear. Thus, they cannot capture asymmetric effects of a shock where the impulse response to a shock can depend on the sign of that shock. Furthermore, the regime-switching VAR models assume that the economy is in a finite number of regimes where the economy can be approximated with linear relationships in each of these regimes. Obviously, if the true data generating process features asymmetric impulse responses, a new set of VAR coefficients are necessary each period. As a result, threshold VARs or Markov-switching models typically require a large number of state variables to capture such asymmetric data generating process. In contrast, the RBF estimator can capture the possibly nonlinear and asymmetric structure of the economy without increasing the number of parameters to be estimated because it does not assume that the economy consists of different regimes. Rather it approximates the possibly asymmetric economy as a whole using a small number of flexible base functions.

The second approach captures nonlinear economic structure by estimating the VAR models using contemporaneous and lagged values of independent variables successively each period of interest. This strand of approach is pioneered by [39] who proposed the "Local Projection method". While Jorda's method can easily capture nonlinearities in the response functions, the Local Projection method poses serious difficulty when its efficiency is considered as pointed as by [8]. Indeed, drawing inferences on a rich set of nonlinearities including sign- and state-dependence using the Local Projection method is often difficult due to its extensive efficiency cost. In contrast, the RBF approach directly approximates the potentially nonlinear data generating process using the neural network based functions that are flexible. Since this approach does not require the estimation of the VARs each period successively, its computational burden does not increase exponentially with the complexity of the data generating functions.

Third and a relatively new approach is proposed by [8] who uses few numbers of Gaussian functions to approximate the impulse functions. Like [39], this approach is robust to functional-form assumtion error but has a great advantage of reduced efficiency costs. The current paper is similar to [8]'s in that both papers utilize the Gaussian functions to approximate macroeconomic structures. The difference lies in that my approach uses the Gaussian functions as a VAR representation as opposed to [8] who use the Gaussian functions in a moving-average (MA) representation.

Finally, this paper is most closely related to [37] who applied the learning networks including the RBFs to financial data and show that network formulas can uncover the structure of the Black-Scholes pricing formula by conduting a Monte Carlo simulations. They conclude that if the structure of data generating process is unknown, the learning networks have high predicting power and can outperform the parametric estimators in terms of out-of-sample prediction. Not surprisingly, the authors report that if the structure of data-generating process is already known to a researcher, the parametric estimators, which assume (correctly) that the data are generated by the Black-Scholes pricing formulas, are always more efficient than the learning networks. The current paper follows [37]'s approach in that I first validate the use of the RBF estimator in the context of macroeconomic time series analysis by conducting a number of Monte Carlo simulation.

2.4 Monte Carlo simulation

To study the large and small sample behavior of the RBFs, I perform Monte Carlo simulation in this section. The challenge I pose in this section is the following: if the structure of the economy was truly determined by a medium-sized nonlinear New Keynesian (NK) model, can the RBF networks capture the structure of NK model? Therefore, I first solve a stylized NK model nonlineary, and simulate data using this NK model to perform Monte Carlo simulation. In the Monte Carlo simulation exercise, I compare the out-of-sample prediction performance of the RBF estimator with the VAR and BVAR models. Subsequent subsections describe the NK model used for the simulation.

2.4.1 Model

The economy is inhabited by four types of agents: Households, Final good producer, Intermediate goods producers, and Monetary authority. Except for the habit persistence in the household sector, the following NK economy is standard.

Households with Habit Persistence

There is a continuum of households who consume a composite good, C_t, supply labour, N_t, and purchase bond B_t. The representative household maximizes the expected lifetime utility given by:

$$E_t\left[\sum_{t=1}^{\infty}\delta_{t-1}\left\{\frac{(C_t-\gamma C_{t-1})^{1-\sigma}}{1-\sigma}+\frac{(1-N_t)^{1-\kappa}}{1-\kappa}\right\}\right] \tag{2.6}$$

where $\delta_t = \beta^t b_t$ is a discounting factor, which is subject to an exogenous preference shock b_t. The shock process for the discounting factor is given by the following:

$$\log(b_t) = \rho_b \log(b_{t-1}) + \epsilon_t^b, \quad \epsilon_t^b \backsim N(0, \sigma_b^2) \tag{2.7}$$

The household is also subject to the following budget constraint each period:

$$P_t C_t + \frac{1}{R_t} B_t = W_t N_t + B_{t-1} + P_t \Pi_t \tag{2.8}$$

where P_t, W_t, and R_t are commodity good price, nominal wage, and nominal interest rates, respectively. In addition, Π_t is the profit from the intermediate-good firms.

We can maximize utility subject to the budget constraint to obtain the optimal allocation of consumption across time,

$$\lambda_t = (C_t - \gamma C_{t-1})^{-\sigma}$$

and

$$\lambda_t = \beta b_t E_t[\lambda_{t+1} R_t / \pi_{t+1}]$$

where $\pi_{t+1} = P_{t+1}/P_t$.

The first order condition concerning labor supply decision is given by

$$W_t = ((1 - N_t)^{-\kappa}/\lambda_t)$$

Final Good Producer

There are perfectly competitive final good producers who use intermediate goods, $Y_t(i)$, for $i \in [0, 1]$ as inputs and produce final good, Y_t, at a price P_t to maximize the profit given by:

$$\max_{Y_t(i)} P_t Y_t - \int_0^1 P_t(i) Y_t(i) di \tag{2.9}$$

The technology of the final good producer is given by the following CES aggregator:

$$Y_t = \left(\int_0^1 Y_t(i)^{\frac{(\eta-1)}{\eta}} di \right)^{\frac{\eta}{(\eta-1)}} \tag{2.10}$$

where $Y_t(i)$ and $P_t(i)$ are quantity and price of an intermediate good i, respectively.

Intermediate Goods Producers

There is a continuum of monopolistically competitive intermediate goods producers who uses labor, $N_t(i)$, as an input and solve the following cost minimization problem:

$$\min_{N_t(i)} TC(Y_t(i)) = W_t N_t(i) \tag{2.11}$$

where TC is nominal total cost. The production technology of the intermediate goods producers are given by the following:

$$Y_t(i) = a_t N_t(i) \tag{2.12}$$

where a_t is the exogenous productivity shock, whose process is given by:

$$\log(a_t) = \rho_a \log(a_{t-1}) + \epsilon_t^a, \quad \epsilon_t^a \backsim N(0, \sigma_a^2)$$

The cost minimization problem of firm i implies

$$mc_t = \frac{W_t}{P_t a_t}$$

where mc_t is the Lagrange multiplier and also the real marginal cost of production.

The intermediate goods producers are also subject to Calvo-type price setting friction. In this environment, only a $1 - \xi$ fraction of the firms set prices optimally each period: $P_t(i) = P_t^*$. Thus, the fraction ξ of the firms are not allowed to change the price, $P_t(i) = P_{t-1}(i)$. The profit maximization problem of a re-optimizing firm i is given by the following:

$$P_t^* \sum_{j=0}^{\infty} \beta^j \xi^j E_t \left\{ \Lambda_{t+j} \left[P_t^* Y_{t+j}(i) - P_{t+j} mc_{t+j} Y_{t+j}(i) \right] \right\} \tag{2.13}$$

where Λ_t is the household's marginal utility of wealth at period t. The intermediate good producers are owned by the household. Thus, all the profits are transferred to the households. The intermediate goods producers solve the optimization described above subject to the demand curve for their own goods given by the following:

$$Y_t(i) = Y_t \left(\frac{P_t(i)}{P_t} \right)^{-\eta} \tag{2.14}$$

Monetary Authority

There is also a monetary authority in this economy who sets nominal interest rate according to the Taylor rule given by the following:

$$R_t = \max\left[\frac{\bar{\pi}}{\beta}\left(\frac{R_{t-1}}{\bar{\pi}/\beta}\right)^{\phi_R}\left(\left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi}\left(\frac{Y_t}{\bar{Y}}\right)^{\phi_y}\right)^{1-\phi_R}, 1\right] \tag{2.15}$$

where $\bar{\pi}$ is inflation target, π_t is inflation rate between $t-1$ and t, and $\bar{Y}$ is the output target. Notice that this monetary authority is subject to the zero lower bound, which means that the monetary authority cannot set nominal interest rate below one.

Aggregate conditions

The aggregate resource constraint is simply given by

$$C_t = Y_t$$

In the Calvo pricing setting, firms that change prices in different periods will have different prices. Therefore, the economy needs to track price dispersion. When firms have different relative prices, there are distortions that create a wedge between the aggregate output measured in terms of production factor inputs and aggregate demand measured in terms of composite goods. Specifically,

$$N_t(i) = Y_t(i)/a_t = \left(\frac{P_t(i)}{P_t}\right)^{-\eta}\frac{Y_t}{a_t}$$

which implies,

$$N_t = \int_0^1 N_t(i)di = \frac{Y_t}{a_t}\int_0^1\left(\frac{P_t(i)}{P_t}\right)^{-\eta}di = \frac{Y_t v_t}{a_t}$$

where price dispersion, v_t, can be described as:

$$v_t \equiv \int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\eta} = \xi \pi_t^{\eta} v_{t-1} + (1-\xi)\left(\frac{P_t^*}{P_t}\right)^{-\eta}$$

2.4.2 Equilibrium conditions

I summarize below the first order conditions that characterize the equilibrium of our economy. Let $p_t^* = P_t^*/P_t$. Then:

$$\lambda_t = (C_t - \gamma C_{t-1})^{-\sigma} \tag{2.16}$$

$$\lambda_t = \beta b_t E_t[\lambda_{t+1} R_t/(\pi_{t+1})] \tag{2.17}$$

$$v_t Y_t = a_t N_t \tag{2.18}$$

$$mc_t = ((1-N_t)^{-\kappa}/\lambda_t)/a_t \tag{2.19}$$

$$C_t = Y_t \tag{2.20}$$

$$R_t = \max\left[\frac{\bar{\pi}}{\beta}\left(\frac{R_{t-1}}{\bar{\pi}/\beta}\right)^{\phi_R}\left(\left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi}\left(\frac{Y_t}{\bar{Y}}\right)^{\phi_y}\right)^{1-\phi_R}, 1\right] \tag{2.21}$$

$$p_t^* = ((1-\xi\pi^{\eta-1})/(1-\xi))^{1/(1-\eta)} \tag{2.22}$$

$$v_t = \xi \pi_t^{\eta} v_{t-1} + (1-\xi) p_t^{*-\eta} \tag{2.23}$$

$$S_t = \lambda_t mc_t Y_t + \beta\xi E_t[\pi_{t+1}^{\eta} S_{t+1}] \tag{2.24}$$

$$F_t = \lambda_t Y_t + \beta\xi E_t[\pi_{t+1}^{\eta-1} F_{t+1}] \tag{2.25}$$

$$p_t^* = S_t/F_t \tag{2.26}$$

2.4.3 Numerical Solution and Simulated Data

The zero lower bound in the Taylor rule introduces a nonlinearity in the NK model. Thus, the solution to the equilibrium condition must be obtained using global numerical methods. In this subsection, I briefly describe the main steps of the algorithm.[2] Let $S = [v_t, C_{t-1}, R_{t-1}, a_t, b_t]$ be the state variables of the model. I use a projection method combined with a clustering method introduced by [50]. Specifically, there are three future variables, $[\pi_{t+1}(S), Y_{t+1}(S), F_{t+1}(S)]$, that need to be interpolated. I approximate each of future variables with the RBFs, $[\pi_{t+1}(\tilde{S}), Y_{t+1}(\tilde{S}), F_{t+1}(\tilde{S})]$, in such a way that equilibrium conditions of the model, detailed in Section 2.4.2, are satisfied at a set of collocation points, $\tilde{S}$. The collocation points, $\tilde{S}$, are selected based on the [50] clustering methods. By using a sparse grid, the curse of dimensionality is greatly reduced when solving the model globally.

Using this nonlinear NK model, I simulated time series data for 100,000 periods. Out of 100,000 periods, the nominal interest rate hits 1093 times.

2.4.4 Generalized Impulse Response

In this section, I examine if the impulse responses estimated by the RBF methods can trace the true structural impulse responses of the nonlinear NK model that is specified and solved above. For the purpose of a clear identification, I assume that the only source of variation in the economy is the discount factor shock. I will give a positive shock (one standard deviation) to the discount factor. Impulse responses are estimated in (1) normal state and (2) zero lower bound (zlb) state.

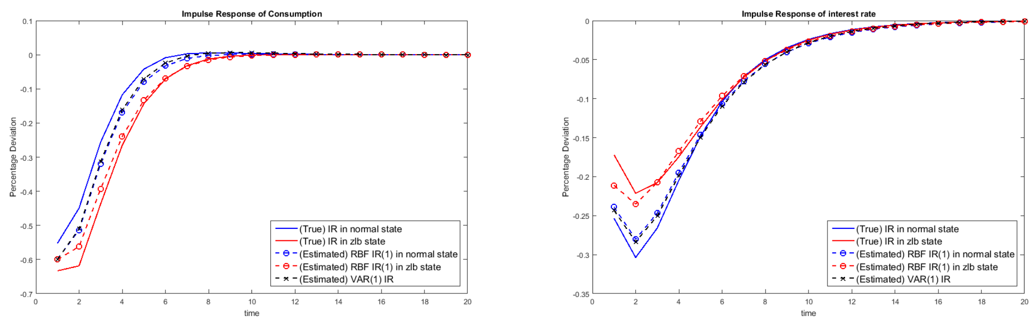
For estimation, I pretend that I observe all state variables: X_t =

[2] See Appendix B.2 and B.3 for the details of the implementation and a discussion of its accuracy.

Figure 2.3: Impulse Responses

training periods = 10,000

(a) Consumption (b) Nominal Interest Rate



$[v_{t+1}\ C_t\ R_t\ b_{t+1}]$.

$$X_t = RBF(\sum_{p=1}^{P} X_{t-p}) + \epsilon_t$$

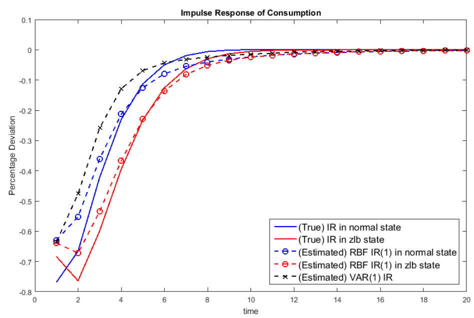
Figure 2.3 shows the results of impulse responses when the length of training set is 10,000. The blue and red solid lines in Figure 2.3 indicate the true impulse responses of the nonlinear NK model in a normal state and a zlb state, respectively. The blue and red dotted lines are the estimated impulse responses of the RBF estimator in the normal and zlb state, respectively. Finally, the dotted black line is the estimated impulse response of a linear VAR. The RBF method correctly captures the difference in the true impulse responses between the normal state and zlb state. Not surprisingly, the impulse responses of a linear VAR only traces the impulse response in the normal state and completely ignores the differential responses of consumption and interest rates in the zlb state. Moreover, the impulse responses by the linear VAR are almost identical to the impulse response of the RBF estimator in the normal state.

In reality, an applied macroeconomist does not have access data that are as large as 10,000. Thus, in the next step, I conducted the same experiment when

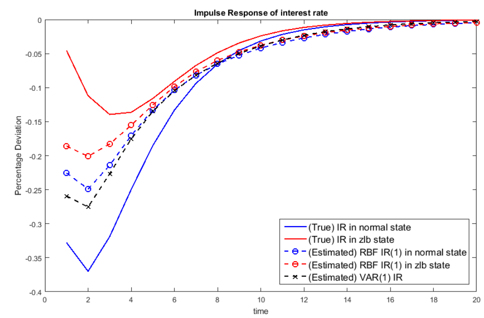
Figure 2.4: Impulse Responses

training periods = 300

(a) Consumption



(b) Nominal Interest Rate



the length of training set is equal to 300. The results are shown in Figure 2.4. The figure highlights that the estimated impulse responses of consumption using the RBF estimator successfully capture both the qualitative and quantitative difference in the responses of consumption between the normal state and zlb state. Again, this is in contrast with the impulse responses of the VAR model where it can only produce the impulse response of consumption that appears to resemble the true response of consumption in the normal state. However, the estimated responses of the interest rates using the RBF estimator underestimates the true impulse response in the zlb state and overestimates the true response in the normal state. The likely reason for failing to capture the magnitude of responses is that the length of the training set in this experiment (300) is not sufficient to trace the sharp kink of the zero lower bound. For the purpose of comparison, the VAR model also suffers from the same problem of failing to capture the magnitude of the drop in the interest rate in the normal state.

2.4.5 Out-of-Sample Prediction Performance

Using the simulated time series data generated by the NK model described above, I calculate, in this Section, the mean-squared prediction error (MSPE) using the RBF estimator, VAR, and Bayesian VAR (BVAR).

The BVAR model was estimated with a prior that combines a Minnesota-type prior (see [46]) with priors that take into account the degree of persistence and cointegration in the variables as in [68]. When setting the tightness of the prior, I chose a set of parameters suggested by [67]. Following [69], I restricted the number of lags in the VARs and BVARs to be one and four, respectively. When choosing the number of parameters in the RBF estimator (i.e. number of centroids), I imposed a restriction that the number of the parameters does not exceed the number of parameters used by the VAR(1) model. Within this constrained parameter space, I chose the optimal number of parameters based on the Bayesian Information Criteria (BIC). In the remainder of this Section, I pretend that I observe only four variables in the simulated data, (i) inflation rate π_t, (ii) output Y_t, (iii) interest rate R_t, and (iv) hours worked N_t. Define $z_t = [\pi_t Y_t R_t N_t]$, then the RBF model can be written as

$$z_t = \sum_{j=1}^{M} K_{\lambda_j}\left(\xi_j, \{z_{t-h}\}_{p=1}^{p}\right)\beta_j + \epsilon_t \tag{2.27}$$

where M, the number of centroids, is determined by the BIC, and $K(\cdot)$ is Gaussian as specified in equation (2.4).

Table B.1 presents the mean and standard error of the Mean-Squared Prediction Error (MSPE) for 1-, 2-, 4-, 8-, and 12-period step-ahead predictions. All models are estimated using 1000 periods of observation (length of training set is 1000), and the number of forecast periods (testing periods) is 60. All models are reestimated each period. The overall measure of forecast performance is the log determinant of the forecast error covariance matrix. The result is based on 1000 Monte Carlo replications, and the standard errors are expressed in the parenthesis.

As in Table B.1, the MSPE produced by the RBF is almost identical to the results produced by the VAR(1) model. The performance deteriorates slowly overall when the number of steps for step-ahead prediction increases in all models, and this is consistent with [69]. Somewhat surprisingly, the MSPE generated by the BVAR(4) is greater than the other two estimators. Thus, with the training set as large as 1000, the RBF estimator performs equally as well as the VAR(1) and BVAR(4) in terms of the out-of-sample prediction errors.

The objective of this Monte Carlo simulation is to study the properties and performance of the RBFs estimator when the data sample is small. I thus performed the same MSPE comparison exercise with the length of training set equal to 300 and 150. The results are reported in Table B.2 and Table B.3, respectively. The results again are based on 1000 Monte Carlo replications.

Almost all the conclusions from Table B.1 still hold true with a smaller training set as observed in Table B.2 and Table B.3. Similar to Table B.1, the overall measure of performance by the RBF and VAR(1) are very close to each other in both Table B.2 and Table B.3. Given that the length of training set is now reduced to 300 and 150, it is somewhat surprising that the overall measure of performance did not decrease by a large amount. It might hint at the fact that the NK model used for this simulation exercise was so simple that an observation set as small as 300 and 150 is enough to capture the true structure of the economy. The results presented in Table B.2 and Table B.3 highlight the fact that the RBF estimator is stable even when using the shorter training sets, and its out-of-sample prediction performance is as good as the VAR(1) and BVAR(4) model even when the length of the training set is as small as 300 and 150. The exercise here illustrates the potential applicability of the RBF estimator to macroeconomic time series analysis.

2.5 Application to the US Data

In this section, I apply the RBF estimator to the US data. I will follow the dataset studied by [69] but extend the dataset to include the fourth quarter of 2013. The last four years of the dataset corresponds to the periods of the ZLB.

2.5.1 Data

[69] consider seven key quarterly macroeconomic US time series as observable variables: (1) the log difference of real GDP, A, (2) real consumption, C, (3) real investment, I, (4) real wage, w, (5) log hours worked, N, (6) the log difference of the GDP deflator, π, and (7) the federal funds rate, R. Consumption, real GDP, real investment, and GDP deflator are obtained from Bureau of Economic Analysis statistics. Hours are calculated by the average weekly hours for all nonfarm business workers (PRS85006023) multiplied by the number of working population (CE16OV) adjusted for the change in labor force participation. Finally, real wage is defined as hourly compensation for all nonfarm business workers (PRS85006103) divided by the GDP deflator.

2.5.2 Impulse Responses

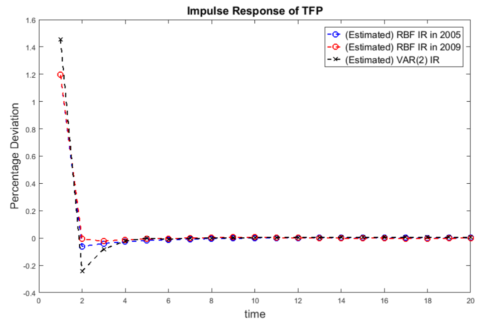
In this section, I estimate the impulse responses of the macroeconomic variables to a positive standard deviation shock to utilization-adjusted TFP, which is measured by Fernald (SF Fed). I estimate the following equations:

$$X_t = RBF(\sum_{p=1}^{P} X_{t-p}) + u_t,$$

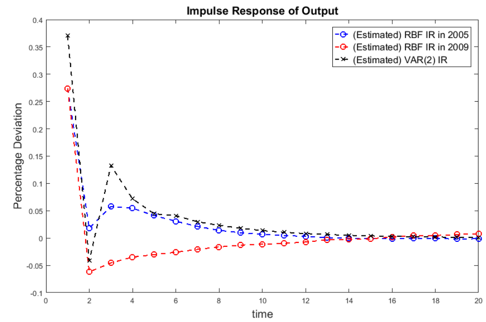
where $X_t = [\Delta A_t, \Delta Y_t, \Delta C_t, \Delta I_t, \Delta w_t, N_t, \pi_t, R_t]$ and $u_t = \left[\epsilon_t^a, \epsilon_t^{m1}, \epsilon_t^{m2}, \epsilon_t^{m3}, \epsilon_t^{m4}, \epsilon_t^{m5}, \epsilon_t^{m6}, \epsilon_t^{m7}\right]'$. Thus, u_t is a vector of reduced form errors. As I am interested in only the TFP shock, I will use the block-recursive assumption suggested by [19] to identify the effect of the TFP shock.

The results are shown in Figure 2.5. The dotted black line is point estimates of the impulse responses using the linear VAR(2). The dotted blue and red lines are the estimated impulse responses using the RBF estimator. As I need to specify exact timing of the shock for the RBF estimator, these responses are estimated to begin in the year of 2005 ("normal state") for the blue line and in 2008 ("zlb state") for red line. The estimated responses of the TFP shock in panel (a) quickly diminish after the period 1. There are two features of the results that need to be highlighted. First, the estimated responses of the RBF estimators in the normal state resemble the responses estimated by the linear VAR(2) with the exception of inflation. This means that, as the linear VAR is expected to pick the structure of economy in the normal state, the RBF estimators in the normal state are capturing the responses of macroeconomic variables in the normal state as intended. The fact the the impulse responses of the VAR(2) and those of the RBF estimators coincide confirms the applicability of the RBF estimator in analyzing

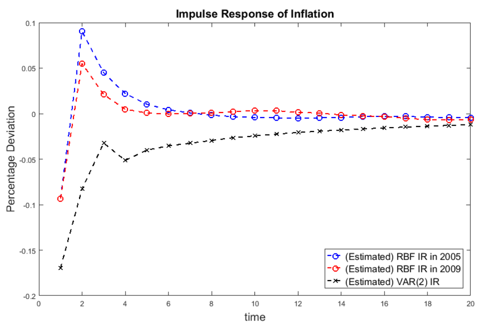
Figure 2.5: Impulse Responses of US Economy



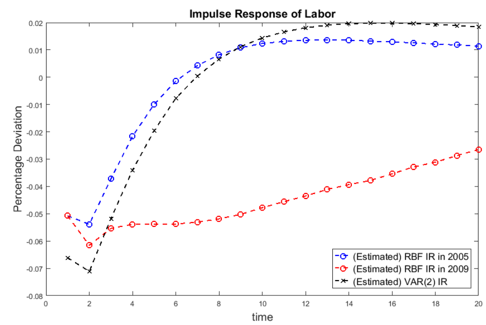
(a) TFP



(b) Consumption



(c) Inflation



(d) Hours worked

the real US economic data. Second, the impulse responses of the output and labor in the zlb state that are estimated by the RBF estimator clearly differ from the responses in the normal state. In particular, the response of labor in the zlb state seems to be much more persistent than the response of labor in the normal state. This hints at the fact that the economy struggles to recover to their steady state due to the inability of the monetary authority to use the interest rates to mitigate the shock. The results suggest that the RBF estimator are capable of capturing different impulse reposes of the macroeconomic variables in the zlb state.

2.5.3 Out-of-Sample Prediction Performance

This Section investigates whether the RBF estimator has a reasonable out-of-sample prediction power even when the estimator is applied to the real US data. For this purpose, I perform out-of-sample prediction performance comparison of the RBF estimator with the VAR(1) and BVAR(4) models. All models are estimated starting in 1955. The forecast period is 1999:1-2013:4, and all models are reestimated each quarter. The overall measure of forecast performance is the log determinant of uncentered forecast error covariance matrix. The result is reported in Table B.4.

Some features of Table B.4 is noteworthy. First, the RBF estimator in general performs poorly compared with the VAR(1) and BVAR(4) in terms of 1 quarter- and 2 quarter-ahead prediction. In particular, the performance is notably worse when predicting the values of investment and hours 1 quarter and 2 quarters ahead. The MSPE obtained from the VAR(1) and BVAR(4) are almost identical in almost all dimensions, with VAR(1) performing slightly better, suggesting that the estimator that has the best out-of-sample prediction power for this dataset is the VAR(1). Even though the RBF estimator performs poorly in terms of the prediction of a short time horizon, its performance improves markedly and does equally as well as the BVAR(4) when predicting variables in 4-, 8-, and 12- quarters ahead. It is not clear what causes the RBF estimator performs relatively well in a longer time horizon, but the results hint at the fact that the RBF estimator has a reasonable predicting power in a long time horizon using the real quarterly US data.

2.6 Conclusion

In this chapter, I investigated potential applicability of the Radial Basis Functions to the macroeconomic time series variables. Based on a stylized New Keynesian model, I performed a number of Monte Carlo simulations to study a large and small sample behavior of the RBF estimator. I found that the RBF estimator can perform equally as well as the traditional time series estimators, i.e., the VARs and BVARs in terms of the out-of-sample prediction. The RBF estimator was also applied to the quarterly US macroeconomic time series data. The performance of the RBF estimator is poor in terms of 1 quarter and 2 quarter ahead prediction, but its performance improves and performs equally as well as the VARs and BVARs when it comes to the 4-, 8-, 12-quarter ahead predictions. In addition, I found that the RBF estimator can capture the quantitative and qualitative differences in the effects of a TFP shock depending on the timing of the shock and economic environments when that shock occurs.

The results shown in this chapter highlights the potential benefit and validity of using the RBF estimator to study time series property of macroeconomic variables. The future work includes the estimation of the government spending multiplier using this RBF estimator.

CHAPTER 3

MARKET SIGNALS AND THE COST OF CREDIT RISK PROTECTION: AN ANALYSIS OF CDS SETTLEMENT AUCTIONS

3.1 Introduction

During the past decade, derivatives known as Credit Default Swap or CDS have become one of the most actively quoted instruments in financial markets. In particular, CDS spreads have mostly replaced bond prices to signal market sentiment vis-a-vis single borrowers, be these corporations or sovereigns. One important, and often quoted, feature of these instruments is that they help isolate pure default risk of a single entity from other factors that may otherwise be affecting the prices of its bonded obligations such as liquidity, market microstructure etc. The relatively lower administrative burden associated with CDS trades have also made them a popular instrument in markets where other instruments are often subject to registration requirements.

Market quotes of CDS "spreads" have become a common measure of default risk. Based on market data, the pricing formulas allow estimating the implied default probabilities of single borrowers. These may then enter the decision making process of market participants and politicians alike. CDS spreads have become widely followed by professionals seeking to extract signals from market data on default probabilities, on liquidity conditions, and also on systemic risk ([2]). The number of empirical studies making use of CDS data has grown considerably in recent times, such as, [49], [74] and [22] among many others.

The objective of this paper is to study whether one of the assumptions made on the models generally used to estimate default probabilities using CDS spreads is appropriate given postdefault data. We also use post-default data to analyze whether the cost of credit risk protection quoted by the CDS market prior to the default reflected appropriately the probability of default as estimated using post-default data.

We thus compare the (*risk-neutral*) default probabilities calculated from CDS spreads through standard valuation models with the probability of default calculated using recovery rates as established by the final bond prices at CDS settlement auctions. We find that adjusting the estimations of the implied default probabilities for the actual recovery rates yields estimates of default probabilities that are significantly different than those estimated using standard assumptions. The implication is that, if quoted CDS spreads are computed using standard expected values on recoveries, market participants may be paying too little or too much for default protection than they would if the default probabilities were estimated using actual recovery values received at the auctions.

Some recent studies analyze whether the recovery values established at the auctions used to settle CDS claims are effective as mechanisms of price disclosure on the bonds underlying the CDS swaps.[1] We investigate the determinants of what we call the "excess spread", the difference we compute between the cost of protection CDS buyers should have been paying given the final bond prices and the actual CDS cost they were charged in the market. We observe "excess spreads" on the cross-section of default experiences where a CDS auction was held. We conclude that large miss-matches between demand and supply of bonds at the CDS settlement auctions may be biasing the final recovery prices of

[1]Examples are [18], who provide a theoretical model for the action process, and [23], [31], and [29], who empirically compare bond prices prior to the auction with the actual auction outcomes, sometimes including the bidding behavior at the auctions

the bonds and thus generating the excess spreads. We also briefly discuss auction participants' payoffs and possible strategic behaviors that may be driving our results.

The rest of the paper is organized as follows: Section I briefly reviews the main characteristics of CDS contracts, the settlement auction mechanism and the main literature on credit event auctions. Section II describes the dataset and the recovery outcomes. Section III presents the econometric methodology and results. Section IV briefly draws some conclusions.

3.2 Brief Review of CDS Contract and How They Are Priced

The term "CDS" refers to an agreement among two parties for the exchange of financial flows. One party agrees to pay a fixed pre-determined periodic amount over the length of the contract. The other party agrees to pay a lump sum only at the occurrence of a specified "credit event" of a third party nominated in the contract ("Reference Entity"). For the contract to exist, the third party or "Reference Entity" does need to have an outstanding obligation ("Reference Obligation") in the form of a bond or a syndicated loan. The "credit event" is legally defined in the CDS contract and encompasses different concepts of a "default".[2] Neither party of the CDS contract needs to hold a "Reference Obligation" in order to enter in the CDS contract, however the financial flows involved in the CDS contract replicate those generated by the holding of securities. For this reason CDS are derivative instruments.

[2]There are several different concepts of "default" in the legal literature and CDS contracts have evolved to incorporate different notions. The most common events are bankruptcy filings or Chap 11 filings in the US, failure to pay, and restructuring. The legal definition of restructuring in most complex and some CDS contracts effectively exclude restructurings.

The cost of a CDS, or premium, may be expressed as an annual amount in basis points.[3] Contracts are usually written for standard maturities, which are, most commonly, of one, three, and five years. Upon the occurrence of a default, a "credit event determination" decision is made by a particular committee of the International Swap and Derivative Association (ISDA) and the CDS settlement procedure takes place through a special "protocol". ISDA establishes the nature of the credit event and the list of deliverable obligations. The securities eligible for delivery are from a single class of debt (senior unsecured bonds, senior loans, and subordinated bonds). The lump sum payment due upon the occurrence of a credit event is set to be equal to the par value of an outstanding obligation issued by the referenced third party, upon delivery of that obligation (or another obligation of similar characteristics).

In the early days of CDSs, after the determination of a credit event, the settlement of CDS contracts took place exclusively through the physical delivery of the reference obligation in exchange of the payment of the full face value amount. The payoff for the party holding the protection claim and the physical obligation will be equal to the face value of the bond less the recovery amount of the security in the market. The party offering the credit protection in exchange for the premium payment would have a cash outflow equal to the face value of the security but would be left holding an asset with a recovery value equal to the market value of the security. The recovery value implicit in the CDS contract (i.e. the value of the reference security after the event of default) was set entirely

[3]Following an ISDA standardization decision, in market quotes the cost of CDSs is many times expressed by the sum of points paid upfront and a "running spread" which has been standardized. For historical record keeping, data is stored in spread terms but the relationship between points and spread is simply related through the standard ISDA model. In other words, it is still possible to back out the "spread" from the points up front using the standard model and standard recovery assumption. In this study we will refer to the "spread" as the cost of the CDS they way it is kept in databases (rather than how it is quoted in the market) to simplify comparisons and for reference purposes.

on the value the protection seller was able to obtain from the security following the settlement of the CDS contract.

However, as the market for CDSs developed, the value of outstanding CDS far outstripped the outstanding stock of debt of the reference entities and this caused issues and concerns at the time these claims had to be settled in the event of default ([31]). The experience during the settlement of CDS contracts on Delphi in 2005 was particularly troublesome as the price of the defaulted bonds increased after the event of default. This occurred because many "naked" protection buyers sought to source the scarce deliverable bonds in the secondary markets. Not only did this give rise to distortions in the securities markets but also yielded highly different payoffs to the different market participants depending on the price they were able to source or sell the reference obligation ([31]).

Following such experiences, ISDA developed a process that aimed at avoiding physical delivery by uniquely establishing the recovery value for the reference obligation and ensure equal payoffs across CDSs buyers.[4] Once the recovery value is uniquely established, CDS contracts can be liquidated on a cash basis without the need to recur to physical delivery.

The procedure developed by ISDA, or "protocol", first entails a decision on whether an entity has suffered a "credit event" and, following such determination, an auction of the bonds of the defaulted entity which are determined to

[4]ISDA has made efforts to harmonize procedures and practices with respect to CDS contracts. It first developed a Master CDS Agreement to standardize contracts. Then, as of 2006, ISDA instituted a protocol for CDS settlement. Whithin this protocol a special ISDA Committee (the credit determination committee) assesses wether an event of default has taken place and then publishes the procedures for the settlement of the claims and the list of deliverable obligations. With the help of Creditex, it was decided that the recovery value for the purposes of liquidation of CDS claims be established through an auction.

be deliverable. In such auction, *all market agents who hold both the security and the protection claim and can participate* by asking to physically deliver the security to claim for the payment of the CDS. In addition, all those agents that have sold protection and require physical delivery of the CDS to settle their dues can ask to participate. All auction participants can require physical delivery of their respective derivative position but no more than that. This implies that a protection holder that desires to settle physically through the auction can commit to deliver no more bonds than those covered by his or hers CDS contracts. This feature is designed to ensure that only CDS buyers with bond holdings participate in the auction and there will be no impact on bond prices from market players needing to source short positions. However, this feature also limits greatly access to the auction by interested parties that might otherwise submit buy or sell orders depending on their estimates of the underlying bond value following the auction.

The auction process occurs in two steps and is best illustrated in [20] and [29], [18], [31]. In the auction process, potential bond buyers (CDS sellers) and sellers (CDS buyers) place their price quotes for bid/offers for the deliverable obligations and their volume requests for physical settlement.[5] An initial mid market point for the security's price is established as well as a Net Open Interest (NOI) for physical settlement requests.[6] In a second stage, buyers and sellers submit their limit orders for the security at the mid market point price. The orders are filled beginning with the higher/lowest price depending on whether the NOI was to buy/sell. The final price at which the NOI is exhausted is the adjusted price for the reference obligation. All CDS claims of agents participat-

[5]The bids/offers contain a certain, pre-established bid/ask spread, and the size of the orders.

[6]The Net Open Interest (NOI) is the net volume of bid (+) and offers (-). That is the only volume that is physically traded at the auction, as the rest is settled in cash.

ing in the auctions are liquidated through the auction mechanism. All other CDS contracts will be settled given the recovery value set at the auction for the reference obligation.

3.2.1 Pricing CDS contract

To illustrate how the post-default recovery prices would influence the valuation of CDS contracts if they were known, we review the basics of the CDS pricing literature ([24], [38], [35], etc.). The CDS contract is identical to a forward sale, by the CDS buyer, of the reference obligation at its face value: i.e. as if it was a default free bond, on the occurrence of a credit event. The CDS buyer or "protection holder" has the right to receive the face value of the reference obligation at a future undetermined date. The protection seller, who agrees to buy forward the obligation as if it were default free, will require to be compensated along the life of the contract for the potential payout it will have to face in the event of a default. The payment he will require should be equivalent to the difference between the market value of the defaulted security and its forward value. In financial terms, the amount of the compensation for the financial risk the protection seller holds will have to be exactly equal to the difference in the yields of a defaultable and default free security. Therefore, extent of the spread that the protection seller will charge will depend on the *risk-neutral* probability of default and also on the post default recovery value.

For the practical purpose of calculating the spread on a CDS contract, we will also remember that the value of every swap must be zero at inception for a market no-arbitrage condition. For this condition to hold, the present value of the stream of payments by the CDS buyer (protection holder) must be equal to the present value of the lump sum payment of the CDS seller (protection seller). As long as the reference entity survives, the CDS buyer will face a pre-established flow of payments, the lump sum payment of the protection seller will occur at an uncertain date and only if the reference entity defaults. We adopt the framework developed by [24], [38], [35] and used by the Bloomberg-developed software to derive the CDS pricing equation. Since these are the most common valuation methods, it is most likely that pricing signals will be extracted by using this methodology.

We note that the CDS buyer will be facing a constant stream of payments S_T, (the CDS spread) for the life of the contract (T) as long as RE, reference entity survives. If we assume that RE has a probability P_t of defaulting at time t and a probability $(1 - P_t)$ of surviving until t, the present value of the stream of payments of the protection buyer over the life of the contract (T maturity of the CDS contract) will be equal to:

$$PV_{\text{Protection Payment}} = S_T \sum_t^T \frac{(1 - P_t)}{(1 + r_t)} \tag{3.1}$$

where r_t is the risk free interest rate at time t.

In the event RE cannot honor its obligations, the protection seller will face a lump sum payment of $(1 - R)$, where R is the recovery rate expressed in percent of par. Defining the probability of defaulting in each period t (discrete) as the probability of default up to period t (Pt) conditional on the probability of having survived until the period before $(1 - P_{t-1})$, it is then possible to express the net present value of the lump sum payment of the protection seller in a discrete time world as:

$$PV_{\text{Payout Payment}} = (1 - R) \sum_{t}^{T} \frac{(P_t - P_{t-1})}{(1 + r_t)} \tag{3.2}$$

Setting the value of the swap to zero, it is possible to derive the equation for the spread of the T period CDS as:

$$S_T = (1 - R) \frac{\sum_{t=1}^{T} \frac{(P_t - P_{t-1})}{1 + r_t}}{\sum_{t=1}^{T} \frac{1 - P_t}{1 + r_t}} \tag{3.3}$$

It is important to note that this equation has two unknowns, one is the probability of default up to period t and the other is the extent of the recovery rate R.[7]

3.2.2 Evaluating Default Probabilities: Reduced-Form Models

The probability of default required for the pricing of the CDS can be modeled as dependent on firms' characteristics (as so-called structural models do) or can be assumed to follow a certain stochastic process (as reduced-form models do). Since structural models of the probability of default are quite complex and often do not fit the data, it is customary in CDS valuation models, to use a reduced-form model assuming as Poisson process with certain assumptions on the hazard rate.[8]

[7]This specification can be easily be transformed for a continuous time environment, but for purposes of our paper, which uses discrete time observations we maintain the discrete time formulation.

[8]By far the most popular model is to assume that the probability of default is a Poisson arrival process with a constant arrival rate. This implies that there is a constant default intensity at every period in time and therefore to expressed as: $P_{it} = \exp^{-\lambda_i t}$ where P_{it} is the probability that entity i defaults at time t and λ_i is the risk-neutral constant hazard rate of entity i, modeled as the arrival rate of a Poisson process. However, this expression entails the assumption that there is a constant default risk to the entire term structure of the different maturities of the reference entities outstanding obligations.

In this study, we concentrate on entities that suffered an event of default. Therefore, the common assumption that the hazard rate is constant does not appear to be appropriate in our case. For this reason, we model the (*risk-neutral*) default probability using a flexible parameterization, used in a number of empirical studies, which allows for a negative slope in the default probability consistent with the intuitive structure for a distressed entity.

For the purposes of this study, we will make use of the formulation used in [51] and [71] which consists of a special case of the functional form proposed by Nelson and Siegel (1987) for the term structure of the default free discount rates. This form is flexible enough to capture both upward and *downward-sloping term structure* that may arise due to stress in the credit markets:

$$\chi_{i,n} = \alpha_i + \beta_i \cdot (1 - \exp^{-t_n})/t_n \tag{3.4}$$

where $\chi_{i,n}$ is the probability of entity i of defaulting in each period n; t_n is the number of years until the cash flow at time n; $\alpha_i + \beta_i$ is the default rate of entity i as t approaches 0; and the infinity maturity default probability is equal to α_t.

Using the specification above it is possible to solve Equation (3.3) after making an assumption on expected recovery rate R. In the most common formulations used by market participants, *the recovery rate is assumed to be a constant fraction of par* at any given period in time (see [12] CDSW function). It thus enters the CDS pricing equation adjusted only for the time value of money. In the most standard formulation it is typically assumed to take a value of 0.4.[9]

[9] It is important to note that there are other types of credit instruments, and in particular LCDS. These are credit default swaps which use outstanding syndicated loans as reference obligations. In the case of loans, the average recovery value as implied in most market software is 70 percent.

This has been set in empirical applications on the basis of the average recovery expectation, as estimated through a large dataset collected and published by Moody's on defaults and recoveries for rated companies ([66]). In this dataset, the long term average of average loss rate on senior unsecured debt is around 60 percent. It is important to note that senior unsecured debt instruments are the type of instruments which constitute the reference obligations in the CDS contracts we are analyzing.[10]

3.3 Data and Empirical Methodology

In this paper we use data from CDS settlement auctions as coordinated and disclosed by ISDA between 2005 and 2014 and run by Creditex.[11] In particular, we use the final published prices of the deliverable bonds by "reference entities", and data on physical request settlements and the related net open interest (NOI see above) at the auction. The auctions are administered by Markit and relevant data is published by ISDA.[12]

In the period between 2005 and June 2014, auctions were held for 116 reference entities for which a credit event was established. There are 156 final auction results, as for some entities more than one auction had to be conducted for different types of referenced obligations (and for different maturity buckets). Data on final recovery prices are available for 93 unsecured notes (senior and subor-

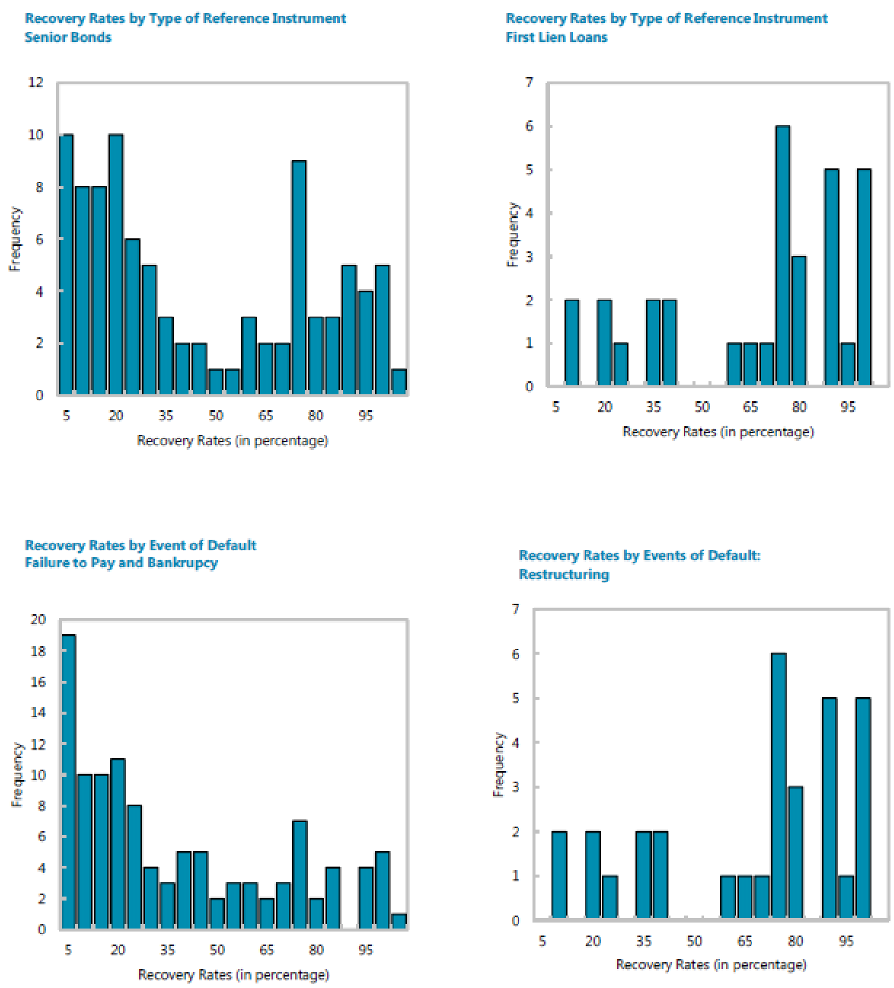
[10]There are a number of papers that review CDS pricing results in light of stochastic recovery rates and conclude that recovery assumptions are crucial for the actual market pricing of the CDS contracts [21], [57] among others.

[11]As of July 2014.

[12]Details can be found at www.isda.org ([70]) and www.creditex.com ([20]).

dinated bonds)[13] and 24 first lien loan obligations.[14] In 73 cases the credit event was determined to be a bankruptcy, in 35 cases there was a failure to pay, and the remainder 32 cases are restructurings.[15]

Figure 3.1: Recovery Rates at CDS Settlement Auctions



Sources: Creditex, ISDA and authors' calculations

1/ Expressed in percent of par values.
2/ Senior CDS: Auction held for deliverable senior unsecured bonds.
3/ LCDS: Auction held for deliverable secured senior loans.

[13] To settle Senior CDS contracts.

[14] To settle LCDS (Loan CDS contracts).

[15] We consider restructurings as a "special" credit event because discussions on recoveries have been taking place prior to the auction. We control for this in some of our empirical estimations.

In the dataset described the average recovery price for senior bonds is 42.74,[16] while for loans it is 51.47, both of which are consistent with standard assumptions on recovery values in CDS valuation models. The data appears also to be consistent with the common notion finance literature that restructurings tend to yield higher recovery rates than outright defaults, including and that recoveries on loans are higher than recovery on bonds.[17] However, while auctions held after "restructuring" credit events, yield significant higher outcomes, on average, than bankruptcies, the standard deviation in the sample is actually rather high.

Data published on the auctions on creditex website also includes the total volume of physical settlement requests, divided in buy and sell orders, and the corresponding net open position (NOI). In particular, we note that, out of the 156 auctions in our sample, 93 have a negative NOI, implying and interest to sell. We also find that the NOIs are highly correlated (0.99) with the total volume of physical settlement requests, suggesting that CDS settlement auctions tend to be "one sided". This is potentially a troublesome feature as auction results may to tend be dominated by large demand and supply mismatches, as suggested in [29], and as predicted by the theoretical models developed by [18] and [23].[18]

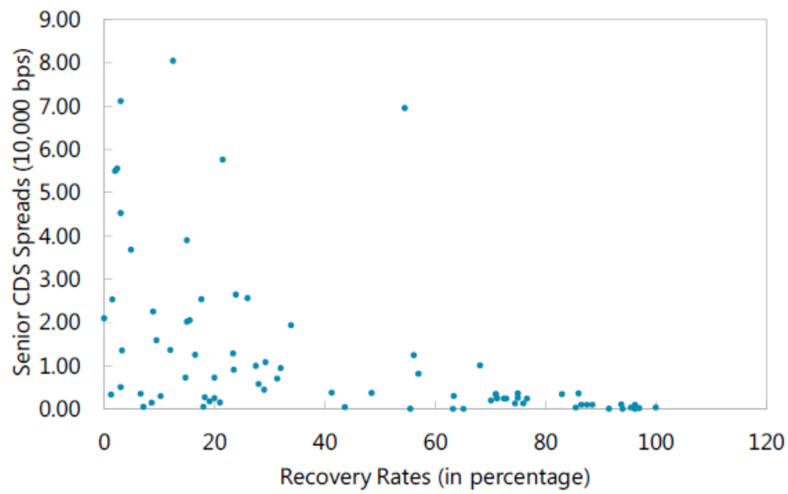
[16]Prices are expressed in percent of par.

[17]Such outcome is consistent with the legal nature of the instrument since loans are normally secured but bonds are unsecured.

[18]The high correlation between NOI and physical settlement requests could be a factor in [29] estimations, who find no significant impact of the NOI with respect to the final bond prices in the auction. In addition their sample is limited to 20 observations.

Figure 3.2: Senior CDS Spreads and Recovery Rates

One year maturity contracts on the day of the credit event



Sources: Creditex, ISDA, Datastream, and Bloomberg.

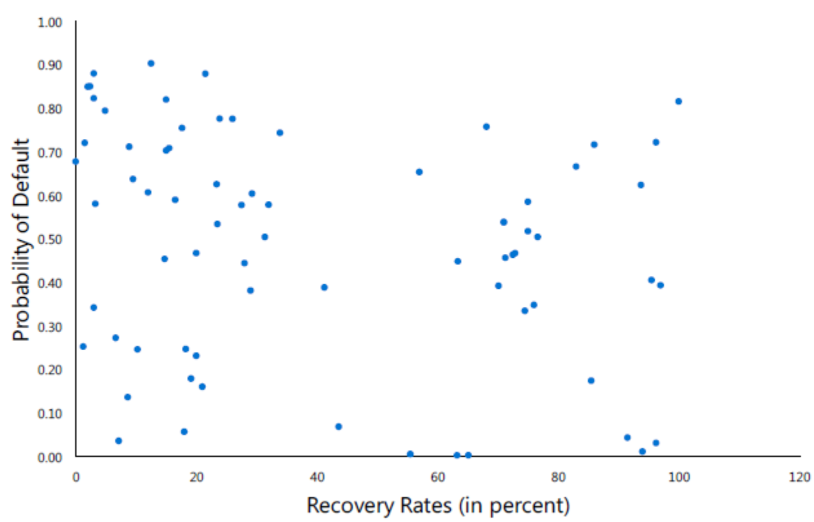
3.3.1 Credit Risk Protection Payments and Implied Default Probabilities

We are interested in the analyzing link between market expectations on default probabilities which determine the CDS spreads prior to the event of default and the actual fair value of default protection as computed from ex-post recovery rates established at the auctions. As a first step, we plot the distribution of the CDS spreads with one year maturity vis-a-vis the final prices of the deliverable bonds at the auctions. This is shown in Figure 3.2. By the nature of the relationship between CDS spreads and recovery rates, we would expect that close to the event of a default, (and for any given default probability) there would be a strong negative relationship between CDS spreads and recovery rates: one would expect to observe higher default probabilities associated with low recovery values and lower default probabilities associated with high recovery values. However, this does not seem to hold for the sample under consideration and there appears to be quite a number of occasions where very low values of recovery rates are associated with very low CDS spreads.

We take another point of view. Since all of the CDS data points in the sample are companies that experienced an event of default observed on the day the credit event was announced, the implied default probabilities should be uniformly high for all the post-default actual recovery rates at the observed spreads. The actual distribution of estimated default probabilities suggests that the market at times has been 'surprised' by the default because lower than average recovery rates were experienced when pre-default CDS spreads were low, implying the expected default probabilities were very low.

Figure 3.3: Implied Default Probabilities One-Year Ahead

Estimated on the day of the credit event using actual recoveries



The commonly held belief that high risk companies CDS' "trade at recoveries" does not appear to hold on the basis of post-default recoveries, since, should that be true, for any given spread, the probability of default should be relatively high for ex-post recovery rates on defaulted companies. On the contrary, a significant amount of data points seems to suggest that, ex-post, the expected probability of default was relatively low.

To analyze the extent of the "surprise" in each credit event, we assume that market expectations are formed using standard recovery rates.[19] Therefore the spreads should reflect the expected probability of default at the standard recovery rates. To gauge the extent to which the probability of default implied by the recovery rates at the auctions differs from the probability of default that would be implied by market quoted spreads at standard assumptions, we use the theoretical relationship between CDS spreads and expected recovery rates (Equation 3.3) to compute ex ante implied probabilities of default. We assume that the CDS spreads on the day of the credit event reflect the best informed default expectations by market participants and that these expectations are formed using average recovery rates on senior unsecured bonds found in [66]s publications therefore imply a recovery value of 0.4. Thus, the expected (risk-neutral) T-years ahead probability of default on the day of the credit event (which we assume is at a maximum) is obtained by solving for $P_{t,\exp}$ given by:

$$S_T \sum_{t=1}^{T} \frac{1 - P_{t,\exp}}{1 + r_t} = (1 - 0.4) \sum_{t=1}^{T} \frac{(P_{t,\exp} - P_{t-1,\exp})}{1 + r_t} \tag{3.5}$$

The term structure of the market quotes for CDS spreads (S_T) allow to compute the marketimplied default probability, as commonly done in empirical literature, solving recursively for the probability of default one-year ahead, three-year ahead etc. (Turnbull, 2003) with a socalled bootstrapping methodology.[20] Following this practice, we computed the marketimplied default probability

[19]Were standard recovery rates are based on historical experiences as published by Moodys and other rating companies.

[20]This is also the standard procedure followed by Bloomberg Corp.

one-year ahead, using data on one year maturity CDS contracts. We use the estimated value for the one year ahead default probability to extract the three year ahead market-implied default probability, and so forth.

We also apply an alternative methodology, as presented in [71], which requires estimating the parameters of a reduced form model for the default probability (Equation 4).[21] We estimate parameters and for each entity that suffered a credit event, under the assumption all market participants have the standard expectation of a 0.4 recovery rate. Both methodologies follow the advice in [25], of using the entire term structure of the hazard rates when estimating default probabilities. We will use both estimations of the implied default probabilities to check for robustness of our results.

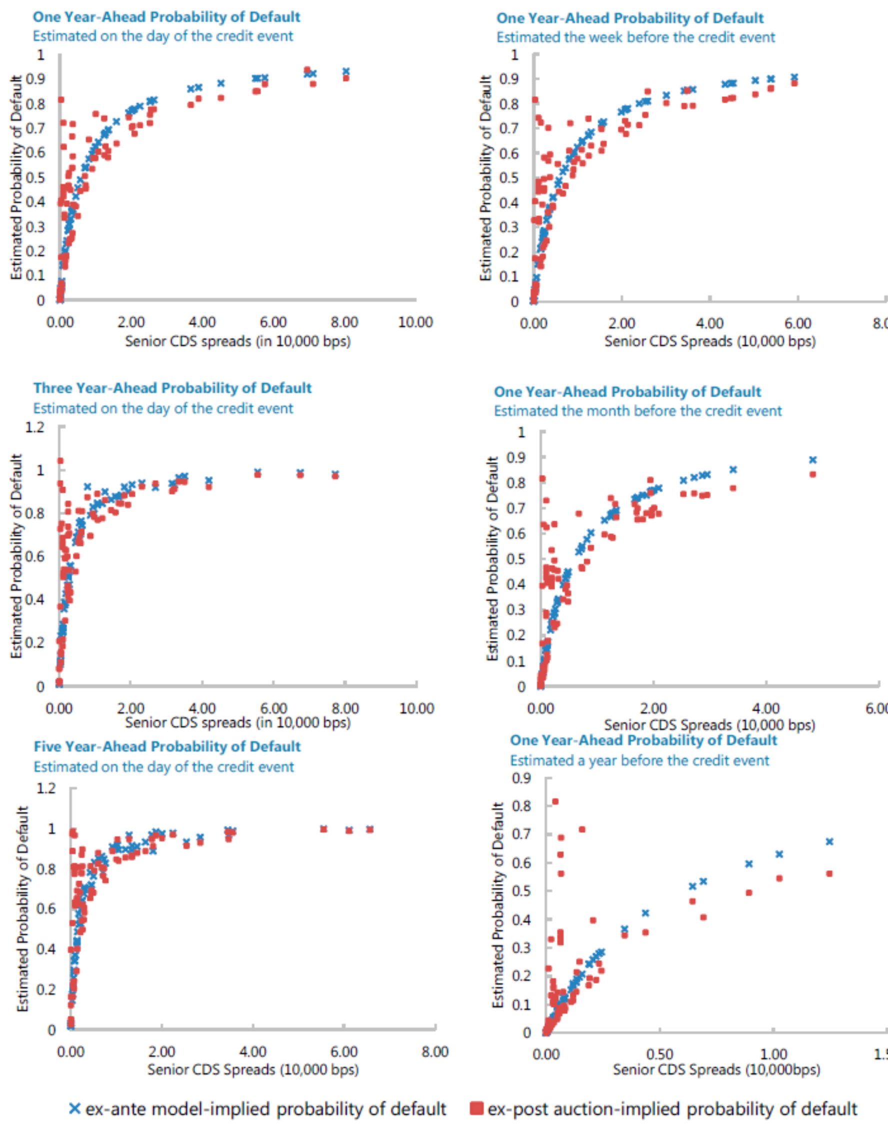
We repeat both the estimations using CDSs spreads observed at dates prior to the event of default and final bond prices at settlement auctions as actual recovery rates. We compare the estimated market-implied default probability consistent with standard signal extracting methodologies with the default probability we would have estimated from the CDS spreads if the final recovery prices form the settlement auctions had been known. We observe how, the default probabilities extracted actual recovery are significantly different with respect to the apriori default probabilities.[22]

To analyze these patterns we chose to compare how different are the market quotes for CDS observed prior to the event of default with those computed assuming that *market participants would have known the actual recovery rates at the*

[21]The alternative methodology assumes a default probability distribution, (so called a reduced-form models), and use the observations on term structure of CDS spreads to estimate the corresponding parameters.

[22]T-stats on pair wise comparison strongly reject the hypothesis of equal means with 99 percent confidence level and reject the hypothesis of same variances at the same significance level.

Figure 3.4: Implied Default Probabilities Estimated Using Average and Actual Recoveries



Source: Authors' calculations.

Note: The red dots in Figure 3.4 depict the probability of default as calculated by applying a standard reduced-form model to actual quoted CDS spreads and using the final auction prices as recovery values, while the blue crosses show the implied probability of default extracted under the assumption of average recovery rates. We extend the analysis of the default probabilities to different CDS maturities to extract the 'one-year-ahead', 'three-year-ahead' and 'five-year-ahead' probability of default. We repeat the calculations, for one week prior, one month prior and one year prior to the credit event date.

auctions. In other words, we calculate the value the protection payments should have had to ensure that, at the inception of the swap, they would have been commensurate with the actual payouts following settlement auction.

We assume that the expected default probability distribution use to calculate the fair value CDS spread will be the same for the observed CDS market quotes and for the recovery values at the auction date. Therefore we can use the quoted CDS spreads over the term structure and the actual recovery rates given the default probability structures estimated from market-quoted spreads.[23]

The final auction prices for the deliverable bonds at the auctions will determine the value of the payment leg of the swap ex-post. This will allow us to compute the CDS spreads that *would have been quoted* by the market if the recovery values of the auction (RA) were known, under the assumption that the markets default probability expectations prevailing prior to the event of default fully reflected all information on the defaulting entity except for the auction results.

$$S_{i,\mathrm{pytR}} = (1 - RA)\frac{\sum_{t=1}^{T}\frac{(P_{t,\exp} - P_{t-1,\exp})}{1+r_t}}{\sum_{t=1}^{T}\frac{1-P_{t,\exp}}{1+r_t}} \tag{3.6}$$

Since the risk-neutral default probabilities are basically a discount weight for the expected recovery rate at the end of the swap period, the difference between the actual CDS spreads and the payout CDS spreads (S_{pytR}) should mainly reflect the difference between actual and expected recovery rates.

If market participants had expected an average recovery rate, we would expect that the difference between the CDS spreads calculated using the payment

[23]The estimated implied default probabilities would be risk-neutral. As these would be the probability of default that would ensure and investor would need to be compensated for to be indifferent between a defaultable and a default-free bond. A wide literature seeks to introduce risk aversion in investor preference and therefore estimate a real world default probability, but this is beyond the scope of our investigation.

leg (average recovery rates) and the payout leg (final auction recovery rates) would *distribute randomly around a zero mean*. This should follow the market efficiency hypothesis, as all information about expected outcomes should be fully reflected in market prices.

We use the data on actual recoveries at the auctions and quoted CDS spreads for one, three and five year maturities quoted on the reference entities at the day of the credit event available in DataStream, Markit and Bloomberg.[24][25][26] We include discount factors from four geographical regions in our dataset that are identified by the 'Determination Committee' at the ISDA as the ones where the predominant trading currency of each reference entity is associated with. These four regions are the U.S., E.U., Great Britain, and Japan. Based on this geographical information, we retrieved one-to-five year risk-free interest rates associated with each reference entity's region from Datastream.

We would expect, a priori, that the relative difference between prices of default protection as calculated before and after a credit event, should follow a random distribution centered on a zero mean, if the standard expectations for recovery rates were based on historical averages. However, we find significant skewness and kurtosis in our sample of recovery rates to reject the normality hypothesis.[27] In CDS valuation terms this implies that the value of the protection leg differs systematically from the value of the payment leg.

We then ask whether the differences in the calculated costs of credit protec-

[24] It is important to note that the reference date for the calculation is the credit event date as determined by ISDA determinations committee and not the day of the auction, as that follows the credit event date by about three weeks. We do not have quoted data for CDS spreads following the credit event date.

[25] www.markit.com

[26] As there are very little quoted spreads data on LCDS (Loan CDS) and CDS related to subordinated debt, our dataset is restricted to 83 observations, only.

[27] See appendix with Summary Tables.

tion before and after the auction still hold for the week, the months and the year prior to the credit event. We thus repeat the same comparison, by using CDS market quoted spreads observed at several dates before the credit event discounting the recovery rate for the appropriate time frame, up to one year before the credit event.

3.3.2 Explaining Auction Outcomes

We use the implied probabilities of default computed above to estimate $S_{pytR,T,i,t}$, the CDS spread that would have prevailed if recovery rates had been known at the prevailing default probabilities. We compute this for the one, three and five year CDS contract maturities. We concentrate in particular on the *one year adjusted spreads at the date of the credit event* as we are interested in observing how well market signals from CDS spreads were anticipating the near-term outcome. We repeat the estimations for all CDS maturities at a number of dates prior to the credit event and up to a year before the credit event.

We define $\Delta S_{T,i,t}$ as $\Delta S_{T,i,t} = \frac{S_{prtR,T,i,t} - S_{T,i,t}}{S_{T,i,t}}$, the "excess spread", as the relative difference between the protection payments we estimated should have prevailed on the basis of the expected default probabilities and the actual recovery rates and the actual CDS spreads prevailing prior to the event of default ($S_{T,i,t}$). We expect that the estimated difference in the spreads will reflect the impact of the actual and expect recovery rates on the implied probability of default and thus give us a measure of the accuracy of the ex-ante market signal as compared to ex-post auction outcomes.

The in-sample properties of the excess spread suggest a non-zero mean (See

Appendix C.2) and a significant skewness. We investigate whether factors at play during the auction may be generating a systematic bias in recovery prices. We conjecture that the excess in spread could be driven both by characteristics of the auction itself and by CDS market and general market sentiment factors that may not have been fully reflected in the CDS prices. In particular, as suggested by [29] and [23] liquidity of the auction itself could be a main driver of the auction prices.

We thus include: (i) a measure of liquidity of the auction itself ([29]; [23], (ii) proxies for market sentiment and the macroeconomic outlook (iii) measures of liquidity of the CDS market for the defaulted entity, (iv) proxy of expectations about the potential future gains from the bonds.[28]

The absolute value of the NOI with respect to the total physical delivery requests can be a good proxy for liquidity as it measures the extent of the miss-match of demand and supply as a share of the size of the market. Our NOI index is thus constructed as the total NOI at the auction as a share of the total sum of bid and offers. The index will be constrained between -1 and +1. We expect that negative values of the index (where the NOI is to sell) will be associated to higher excess spreads (because the lower than expected bond prices will require higher CDS spreads). By contrast, lower and negative values of the excess spread should be associated with either small mismatches or a NOI to buy which would potentially drive auction prices above market expectations. This is actually reflected by the in-sample correlations (See Appendix C.2).

We include controls to proxy for liquidity in the CDS market for the defaulted entities: (i) the number of CDS contracts outstanding on the day of the

[28]The list of variables and definitions is included in the Appendix C.1.

credit event, and (ii) the share of netnotional values of CDS to gross notional values on the day of the credit event, this is a measure of liquidity in the CDS market for the entity.[29] This share provides a measure of how many times the CDS contracts have been re-sold in the market, given a certain notional outstanding.[30]

We also include controls to proxy for general markets sentiment at the time of the auction that could be influencing recovery prices, in particular: the CBOE volatility index (VIX) as a proxy of the amount of risk aversion in the system at the time of the credit event; the total amount of defaults per year, as proxy for recessions and the general business cycle;[31] the prevailing 3 month libor rates at the time of the credit event, a proxy for the monetary policy stance; and, the US 5 year zero coupon rates at the time of the credit event, a proxy for long term expectations about the state of the economy.[32] We also include a variable to account for market expectations about the possibility of recovery of the defaulted entity.[33]

[29]The Gross notional values of CDS outstanding registered in DTCC have been declining as accounting for CDS positions has improved. We consider that taking the share of Net notional values to Gross notional values avoids then problem generated by the structural trend.

[30]The weekly data can be retrieved from Trade Information Warehouse Report on Depository Trust & Clearing Corporation (DTCC) website. However, these data are available for only the top 1000 reference entities in terms of trading volume each week. As a result, we have 59 observations for these proxy variables for CDS markets' liquidity.

[31]Total number of Chap.11 filings per year, in Datastream

[32]For the US, UST zero coupon yield were used, for the EU, EU vs EONIA zero swap rates were uses, for Japan and UK, zero coupon rates bonds were used. Data for interest rates, bankruptcies, as well as VIX were all obtained from DataStream.

[33]One way to do this is to include the 5-year CDS spreads in the set of regressors. However, directly including 5-year CDS spread as a regressor might yield spuriously significant results, since the 5 CDS spreads also depend on the 1 year spreads. To address this concern, we first regress 5-year CDS spread on 1-year CDS spread and 3-year CDS spread as specified: $\text{y5 CDS spread}_t = \alpha_0 + \alpha_1 \cdot \text{y1 CDS spread}_t + \alpha_2 \cdot \text{y3 CDS spread}_t + \text{controls}_t + \omega_t$. The resulting residuals represent a variation in 5-year CDS spread that is independent of all the information contained in 1-year CDS spread and 3-year as well as other control variables such as NOI index, defaults per year and sector fixed effects. We use this residual, ω_t, as a proxy for long-run default probability that is independent of short-run default probability.

Finally, we construct a categorical variable that identifies industrial sector of each reference entity. This sector-specific variable was constructed by retrieving two-digit NAICS code for each reference entity. In our dataset, each entity falls into one of the following 15 industries.[34]

Our empirical specification is the following:

$$\Delta S_{T,i,t} = \frac{S_{prtR,T,i,t} - S_{T,i,t}}{S_{T,i,t}} = \beta_0 + \beta_1 \cdot NOIIndex_{i,t} + \beta_2 \cdot \text{Risk Aversion}_t$$

$$+ \beta_3 \cdot \text{Control}_{i,t} + \sum_{s=1}^{5} \gamma_s \cdot \text{Industrial Sector}_{i,s} + \epsilon_{T,i,t}$$

We call $\Delta S_{T,i,t}$ the excess spread that would be necessary to add to market quoted rates to ensure that two legs of the CDS are appropriately valued after accounting for actual recovery rates. T indicates the maturity of the CDS contract, t the time at which the spreads are observed, i is the defaulting reference entity indicator. We concentrate on the auction characteristics (NOIindex) as our main explanatory variables because we assume that all market available information is already reflected in the CDS quoted prices. We conjecture that if the final recovery rate has a systematic bias, this may signal the presence of strategic behavior by auction participants.

We use ordinary least squares and include fixed effects at the industry level, fixed effects for the year of default, and we adjust for clustered standard errors.

[34](i) Administrative and Support Services, (ii) Arts, Entertainment, and Recreation, (iii) Construction, (iv) Finance and Insurance, (v) Information, (vi) Management of Companies and Enterprises, (vii) Manufacturing, (viii) Mining, Quarrying, and Oil and Gas Extraction, (ix) Professional, Scientific, and Technical Serivices, (x) Other Services except public administration (xi) Public Administration, (xii) Real Estate and Rental and Leasing, (xiii) Retail Trade, (xiv) Transportation and Warehousing, (xv) Utilities.

Results of the estimations are reported in Tables 3.1, 3.2, 3.3 and 3.4.[35][36]

Table 3.1: Determinants of Excess Spreads - Baseline REgressions

Dependent Variable:			$\Delta S_{1,CE}$			
	(1)	(2)	(3)	(4)	(5)	(6)
NOIindex	-0.410***	-0.352***	-0.354***	-0.333***	-0.195**	-0.300***
	(0.0559)	(0.106)	(0.0787)	(0.0853)	(0.0854)	(0.0576)
VIX			0.0178**	0.0162*	0.0155**	0.0155**
			(0.00646)	(0.00751)	(0.00630)	(0.00529)
Constant	-0.146***	-0.460***	-0.646***	-0.730***	-0.405*	-0.532***
	(0.0135)	(0.0671)	(0.178)	(0.214)	(0.181)	(0.135)
FE (Auction Year)	No	Yes	No	No	No	No
FE (CDS region)	No	No	No	Yes	No	No
FE (Industry)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72	72	72	72	59	84
Sample 1/2/	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Excl. Restr.	Full Sample
R-squared	0.205	0.401	0.368	0.396	0.257	0.270
Adjusted R-squared	0.193	0.314	0.349	0.360	0.230	0.252

1) Standard errors in parentheses. Significance: * denotes probability level p¡0.10; ** p¡0.05; and *** p¡0.01". Estimations using reduced form probability structures, and robust standard errors. See Appendix C.2 for variable sources and definitions. 2) Dependent variable, excess CDS spread, one year maturity: $(S_{prtR,t} - S_t)/S_t$

Notes: The baseline regressions are shown in Table 3.1. Dependent variable: excess spreads at one year maturity computed using reduced form probability structures. In column (1) the excess spread is regressed on the NOIindex for the sample of auctions on senior bonds, including fixed effects included only for the industry of belonging of the defaulting entity;(2) include fixed time effects for the year of default; (3) includes a control for market volatility at the time of default and makes which makes the inclusion of time effects not necessary; (4) includes regional effects for CDS markets; (5) excludes all those credit events that occurred as a result of a restructuring decision between the defaulting entity and its creditors; (6) includes the auctions on subordinated bonds.

We find that our NOIindex has a large negative association with the excess spread, which is statistically significant at conventional levels. This requires some interpretation. It is important to remember that a positive NOI suggests that the volume of demand for the defaulted bonds is in excess of the supply, the reverse when it is negative. A positive excess spread suggests the payment leg of the CDS underestimated the ex-post the recovery rates at the auctions, or,

[35] A formulation of the dependent variable in logarithmic formulation was tried, all significance was maintained.

[36] Results presented are for excess spreads computed using reduced form probability structures. The same regressions were also run with excess spreads computed using bootstrapped probabilities; the results did not change significantly.

Table 3.2: Determinants of Excess Spreads - Additional Controls

Dependent Variable:				$\Delta S_{1,CE}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NOIindex	-0.359***	-0.352***	-0.413**	-0.416***	-0.351***	-0.352***	-0.250***	-0.248***
	(0.0899)	(0.0722)	(0.154)	(0.112)	(0.0779)	(0.0792)	(0.0731)	(0.0141)
VIX	0.0194*	0.0176**	0.0123	0.0112**	0.0172**	0.0175**	0.0130	-0.0103
	(0.0100)	(0.00701)	(0.00789)	(0.00454)	(0.00616)	(0.00632)	(0.00856)	(0.0179)
default year	-0.000385							
	(0.00161)							
3 month libor		0.00525						
		(0.0289)						
N.CDS contracts (DTCC)			-0.0000					
			(0.00001)					
NetNotional Index				1.064				
				(2.063)				
Zero coupon 5 year rates					-2.059			
					(4.275)			
Default prob. 5 year ahead (instr.)						0.120		
						(0.194)		
Avg Price Bonds							-0.00587**	
							(0.00209)	
Price 1 year Bonds								-0.00602
								(0.00447)
Constant	-0.643***	-0.646***	-0.434	-0.493	-0.675***	-0.638***	-0.162	-0.242
	(0.163)	(0.175)	(0.342)	(0.269)	(0.185)	(0.173)	(0.352)	(0.447)
FE (Auction Year)	No	No	No	No	No	No	No	No
FE (CDS region)	No	No	No	No	No	No	No	No
FE (Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72	72	48	48	72	72	53	32
Sample 1/	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS
R-squared	0.370	0.368	0.356	0.360	0.369	0.370	0.566	0.699
Adjusted R-squared	0.342	0.340	0.312	0.317	0.341	0.342	0.539	0.654

1) Standard errors in parentheses. Significance: * denotes probability level p¡0.10; ** p¡0.05; and *** p¡0.01”. Estimations using reduced form probability structures, and robust standard errors. See Appendix C.2 for variable sources and definitions. 2) Dependent variable, excess CDS spread, one year maturity: $(S_{prtR,t} - S_t)/S_t$

Notes: Table 3.2 shows results of regression assessing robustness of the baseline regressions controlling for omitted variables. Dependent variable: excess spreads at one year maturity computed using reduced form probability structures. All regressions are run on the sample of auctions on senior bonds. For variables definitions see Appendix C.1.

Table 3.3: Estimation Using Five-year Ahead Implied Probabilities of Default

Dependent Variable:	$\Delta S_{5,CE}$	$\Delta S_{5,CE}$	$\Delta S_{5,CE}$	$\Delta S_{5,CE}$	$\Delta S_{1,CE-1y}$	$\Delta S_{1,CE-1y}$	$\Delta S_{1,CE-1y}$	$\Delta S_{1,CE-1y}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NOIindex	-0.399***	-0.323**	-0.343***	-0.324***	-0.416***	-0.357**	-0.384***	-0.329***
	(0.0541)	(0.106)	(0.0795)	(0.0850)	(0.0685)	(0.116)	(0.0846)	(0.107)
VIX^{+}			0.0178**	0.0163*			0.00956***	0.0162**
			(0.00643)	(0.00744)			(0.00201)	(0.00735)
$VIX\_1y^{\#}$							0.00442	-0.00681
							(0.00784)	(0.00792)
Constant	-0.148***	-0.466***	-0.647***	-0.719***	-0.148***	-0.438***	-0.523* -	0.550
	(0.0131)	(0.0706)	(0.176)	(0.208)	(0.0152)	(0.0560)	(0.243)	(0.484)
FE (Auction Year)	No	Yes	No	No	No	Yes	No	Yes
FE (CDS region)	No	No	No	Yes	No	No	No	No
FE (Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72	72	72	72	76	76	76	76
Sample 1/	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS	Senior CDS
R-squared	0.196	0.399	0.359	0.380	0.195	0.378	0.261	0.434
Adjusted R-squared	0.184	0.311	0.341	0.343	0.184	0.294	0.230	0.229

1) Standard errors in parentheses. Significance: * denotes probability level p¡0.10; ** p¡0.05; and *** p¡0.01". Estimations using reduced form probability structures, and robust standard errors. See Appendix C.2 for variable sources and definitions. 2) Dependent variable, excess CDS spread, one year maturity: $(S_{prtR,t} - S_t)/S_t$, 3) +: VIX at the auction date, 4) #: VIX at the CDS spreads observation date

Notes: Table 3.3 shows regressions assessing robustness by using as a dependent variable the excess spread computed for five year maturity CDS contracts on the day of the credit event and the same excess spread observed a year before the credit event on the sample of auctions for senior bonds.

ex-post, the probability of default should have been higher, a negative excess spread suggests the contrary. Empirical evidence suggests that at the auctions with significant sell interest (negative NOI) the excess spreads tend to be higher (positive $\Delta S_{T,i,t}$) and thus actual bond prices were below market expectations. By converse, when the volume of demand is greater than supply (positive NOI), a negative impact suggest that excess spread reduces (negative $\Delta S_{T,i,t}$), as final bond prices tend to be above standard market expectations and, ex-post, the probability of default should have been lower. The estimated coefficients sug-

Table 3.4: Estimations Using Excess Spreads at Different Dates

Dependent Variable:	$\Delta S_{1,CE-1m}$	$\Delta S_{5,CE-1m}$	$\Delta S_{1,CE-1y}$	$\Delta S_{5,CE-1y}$
	(1)	(2)	(3)	(4)
NOIindex	-0.366***	-0.345***	-0.412***	-0.425***
	(0.0935)	(0.102)	(0.0819)	(0.0755)
VIX_1m^+	0.0149**	0.0152**		
	(0.00517)	(0.00517)		
VIX_1y^+			0.00473	0.00489
			(0.00583)	(0.00589)
Constant	-0.555***	-0.563***	-0.273	-0.266
	(0.145)	(0.145)	(0.153)	(0.153)
FE (Auction Year)	No	No	No	No
FE (CDS region)	No	No	No	No
FE (Industry)	Yes	Yes	Yes	Yes
Observations	76	76	76	76
Sample 1/	Senior CDS	Senior CDS	Senior CDS	Senior CDS
R-squared	0.269	0.254	0.190	0.201
Adjusted R-squared	0.249	0.234	0.168	0.179

1) Standard errors in parentheses. Significance: * denotes probability level p¡0.10; ** p¡0.05; and *** p¡0.01". Estimations using reduced form probability structures, and robust standard errors. See Appendix C.2 for variable sources and definitions. 2) Dependent variable, excess CDS spread, one year maturity contracts: $(S1_{prtR} - S1_t)/S1_t$ and excess CDS spreads on five year maturity contracts: $(S5_{prtR} - S5_t)/S5_t$. 3) +: VIX at the auction date

Notes: Table 3.4 presents estimation results for the determinants of excess spreads when calculated on CDSs for one year and five year maturity contracts, observed the month and the year preceding the credit event. The same regressions were run with three year maturity contracts, results were not significantly different.

gest that an increase in the size of the NOIindex by 1 would reduce the size of the excess spread by around 30 percent. As an example, an auction for a bond of a defaulted entity where the NOIindex is to sell would experience an excess spread 30 percent higher than an auction with the same magnitude NOIindex but an interest to buy. A qualitative change in the structure of the auction (from sell to buy) at the same magnitude of volumes and NOI generates significantly higher recovery values.

This result suggests that large miss-matches between supply and demand appear to be affecting prices at the auction, and that the minority group at the auction will see a bias of prices in its favor. Such results appears to be in line with the claim in [29] that illiquidity at the auctions is biasing final recovery prices, where illiquidity is seen as the lack of buyer/sellers, so that, in order to "win the action", bids and offers are biased.[37] We also find evidence that market sentiment (VIX) is important at the time of default, and with the right sign: the higher the market volatility at the time of default, the lower the recovery prices with respect to expectations. However, the impact of interest rates and the broader macroeconomic outlook are limited. This result is in line with the expectation that information known to market participants prior to the auction should have influenced the CDS quote and therefore should not have any impact on auction prices. Interestingly, none of the indicators of liquidity in the CDS markets appears to have any influence on the spread differential. This suggesting that the total volume of physical delivery requests is completely independent of the overall micro-structure of CDS market for each defaulted entity.

Finally, the variable to control for the expected price of the bond after final bankruptcy procedures was significant if taken as an average of observed prices. However, the price of the bonds of one year remaining maturity was not significant when clustered errors were used, likely because of significant dispersion in the data.

[37]Their study focuses on the difference between deliverable bond prices prior and after the auction and the auction final prices. We assume that part of that difference has to be reflected in the implied default probability as calculated prior to the auction and using the auction results.

3.3.3 Discussion of Results

The question remains open as to why auctions tend to display relatively large NOIs and in particular, why they tend to be NOIs to sell. One possible explanation is that relative payoffs of bidders and sellers *at the auctions* with respect to their bond and CDS positions has a tendency to generate sell NOIs. We suggest that the auction structure tends to reduce the number of potential bond buyers and therefore yields sell NOIs.

This is better discussed when thinking at the different payoffs generated by the decision between cash settlement and physical delivery. A CDS seller that chooses to settle physically will place a buy order. After the auction he will face payments for 100 on his CDS positions will be delivered bond with an auction price of R. Assuming he sits through the bankruptcy proceedings and in final liquidation is awarded a cash payment of Fr, his total payoff from choosing to settle physically will be equal to the difference between the auction recovery value and the final payout after bankruptcy or resolution the credit event.[38] A CDS seller will thus choose physical delivery only those occasions in which she expects that after the auction i.e. for example bankruptcy proceedings, the payout will be higher than the auction price.[39] If she expects that auction prices will be close to the final payout value of the bond, she will be indifferent between physical delivery and cash settlement, and thus *might not enter the auction*. If the CDS seller believes that the final liquidation value will be lower than the auction price, then she would be better off by *not choosing physical delivery* and

[38]Actually, not all credit events imply bankruptcy procedures to follow the auction. Indeed a significant number of them are connected to restructuring decisions. While we use the language “final payout” here, it is intended to refer to the expected value the obligation will have following the auction.

[39]The reasoning is not different if we assume there is a secondary market for the defaulted bonds after the auction has taken place and CDS sellers can sell their bond.

simply paying 100-*R* in cash settlement.

A CDS buyer that chooses to physical delivery needs either to own or to source the bond to sell at the auction. If she settles in cash she will then receive a payout in the size of the net loss after default (100-*R*). The only cases in which the CDS buyer will secure a higher return from not participating in the auction is when she expects the price of the auction to be lower than what she will receive from final payout or lower than the market price at which she can source the bond.

To summarize the strategies, the optimal behavior for CDS sellers would be not to join the auction at all unless there is an expectation that final liquidation values are significantly above the auction prices.[40] Similarly, the only cases in the CDS buyer will not participate in the auction will be if the auction price established at the auction is lower than the purchasing value of the bond and/or the final payout price. So CDS buyers will participate in the auction if they expect final payout values to be lower than the auction prices but CDS sellers will not.

Auction behavior

As both CDS buyers and sellers will tend to go long or short the physical bond at the same time, there will be a tendency of the auction to reflect the expectations of the market in terms the final bond payout values. Should the market, on average, expect low payout values, then the a NOI will be to sell, by contrary if market expectations are for high payout values then the NOI will be

[40]The CDS seller that does join the auction has an interest in securing low auction recovery prices, she has no interest minimizing her CDS payout because only *what she expects to get after the auction*, will determine her bidding at the auction. The actual final price of the action *R does not enter the total payoff*

to buy. This could explain why NOIs at the auction tend to be highly correlated with the auctioned volumes, as market expectations on the final liquidation values reduce the amount of auction participants.

If we assume that expectations on *final liquidation values* distribute normally in the market, with the expected value being the median and the mode of the distribution, then, at each auction, only a minority of agents will be taking different views from those prevailing in the market. Therefore, for any given expected *final liquidation value* agents with the majority view will tend to over/under bid, in order to "win" the auction. This behavior would be in line with the theoretical models of [18], [23]. So that, eventually, the minority of buyers/sellers that have expectations different from the rest of the market will be able to achieve an auction price in the direction that will ensure they have a positive payoff by participating in the auction.

3.4 Conclusion

This paper contributes to the growing empirical research on the auctions used to settle CDS positions following the occurrence of a credit event. We have found evidence that the difference between actual and expect recovery rates on the required CDS spreads, given default probability expectations, would yield to a systematic bias in the ex-ante market signal of implied probabilities of default. This implies that, should CDSs pricing in the market follow standard modeling and assumptions, there has been a systematic bias in the valuation of the two legs of CDS contracts when compared with the ex-post recovery values of the bonds at the auctions.

We have analyzed the difference in valuations between the two legs of the CDS contract by calculating the excess spread that should have been charged on the basis of the actual recovery rates and expected default probabilities as signaled by market prices prior to the credit event. We have found that both the size of the Net Open Interest at the CDS settlement auction and market sentiment in general tend to have a significant impact on the size of the excess spread. In particular, we find that the NOI at the auctions is inversely associated with the size of the excess spread, suggesting that large miss-matches between supply and demand at the auctions tend to bias auction prices. Our findings are consistent with the evidence in [29] who find that final auction prices of the deliverable bonds tend to be below their pre- and post auction fair market values.

We explain this result by analyzing the payoffs of the CDS sellers and buyers at the credit event and we conclude that the nature of the strategies is such that auctions tend to be "one sided" and therefore to "win" the auction the bids will tend to come in below or above the target price depending on the sign of the net open interest. In addition, we conjecture that the buy side interest at the auction will tend to be limited both because of the particular specialized nature of investors in defaulted bonds and because of the auction' own regulations. These preclude potential bonds buyers from entering the auction absent a sell CDS position. CDS sellers that chose not to settle physically a lower than the fair value prices choose to incur such a loss to avoid withstanding bankruptcy proceedings but thus face higher than expected payouts.

Several interesting avenues for future research remain open. One is to identify a fully fledged model for auction behavior along the lines of [18] and Du-Zhu (2013) that includes the expectations on the final payout from bonds and

CDS positions after the auctions in the reaction function of market agents. The other is to extend our analysis using data on actual CDS spreads (rather than quoted spreads) as charged and valued by market dealers. Should our results be confirmed, the auction mechanism might need to be rethought, especially if there are significant volumes of CDS sold which are settled in cash because the protection sellers are not active in managing their portfolios and may have little incentive in participating in post-auction bankruptcy procedures.

APPENDIX A

CHAPTER 1 APPENDIX

A.1 Data Description

Throughout the analysis, I used the Japanese Household Panel Survey (JHPS) and the Keio Household Panel Survey (KHPS). The original datasets include approximately 4000 households between 2004 to 2008 and 8000 households between 2009 and 2014. I focus on the income of sub-sample of the household-heads who were recorded at least 4 times. This criterion leaves us with about 2000 samples each year from 2004 to 2008 and about 3200 samples from 2009 to 2013.

The survey records the labor income of household-heads under the following four categories: (i) monthly wages, (ii) weekly wages, (iii) hourly wages, and (iv) annual bonuses. I construct an estimated hourly wages based on all four measures of the wages.

The monthly wages and annual bonuses are converted into hourly wages by the following procedure:

$$\text{hourly wages} = \frac{\text{monthly wages} + \text{annual bonuses} \ / \ 12}{(\text{average days worked per month}/4.381\ \text{weeks}) \times \text{hours of work per week}}$$

The denominator is the hours worked per month, which is estimated using the reported average days worked per month, the average number of weeks in a month (4.381 weeks), and the reported hours of work per week.

The weekly wages are converted into hourly wages by the following procedure:

$$\text{hourly wages} = \frac{\text{weekly wages}}{\text{hours of work per week}}$$

A part of the job-tenure is also estimated for the analysis. The survey asks respondents the year in which they started the current employment. From this figure, I calculate the job tenure. However, this question is available only when the respondents enter the survey for the first time. For the following years, I add a year to the job tenure if the respondents reported that they stayed at the same workplace from previous year. Otherwise, I set the job tenure to 0.

The work experience is constructed in a similar manner. The number of years working is reported only when the respondents are recorded in the survey for the first time. From this, I add a year to the work experience if the respondents reported that they worked in the following years. Otherwise, the work experience in each survey year remains the same as the previous year.

A.2 Stationary Inducing Transformation

This section shows the derivation of the stationary inducing transformation and that the value functions are homogeneous of degree one in X. Let variables in *tilde* indicate the variables before the stationary-inducing transformation. Without loss of generality, I assume no human capital accumulation, $\pi_j = 0$ for $j \in \{\text{perm}, \text{temp}, \text{u}\}$, and no outside wages for permanent workers.[1] The system of value functions before conducting the stationary-inducing trans-

[1]Under this assumption, the permanent firms incur firing costs as soon as firms and workers meet at the initial period of employment.

formation is:

$$\tilde{U}(h) = \tilde{b} + \beta(1-\nu)\max \mathbb{E}\left[\tilde{U}'_{\text{perm}}(h), \tilde{U}'_{\text{temp}}(h)\right] \tag{A.1}$$

$$\tilde{U}_{\text{perm}}(h) = f(\theta_{\text{perm}})(\tilde{W}_{\text{perm}}(h) - \tilde{U}(h)) + \tilde{U}(h) \tag{A.2}$$

$$\tilde{U}_{\text{temp}}(h) = f(\theta_{\text{temp}})(\tilde{W}_{\text{temp}}(h) - \tilde{U}(h)) + \tilde{U}(h) \tag{A.3}$$

$$\tilde{J}_{\text{perm}}(h) = h \times X - \tilde{w}_{\text{perm}}(h) + \beta(1-\nu)\mathbb{E}\left[(1-\delta_{\text{perm}})\tilde{J}'_{\text{perm}}(h) - \delta_{\text{perm}}\tilde{\phi}'\right] \tag{A.4}$$

$$\tilde{J}_{\text{temp}}(h) = A \times X - \tilde{w}_{\text{temp}}(h) + \beta(1-\nu)\mathbb{E}\left[(1-\delta_{\text{temp}})\tilde{J}'_{\text{perm}}(h)\right] \tag{A.5}$$

$$\kappa_{\tilde{\text{perm}}} = \beta(1-\nu)\mathbb{E}\left[q(\theta_{\text{perm}})\int_h \tilde{J}'_{\text{perm}}(h)d\mu^h_{\text{perm}}\right] \tag{A.6}$$

$$\kappa_{\tilde{\text{temp}}} = \beta(1-\nu)\mathbb{E}\left[q(\theta_{\text{temp}})\int_h \tilde{J}'_{\text{temp}}(h)d\mu^h_{\text{temp}}\right] \tag{A.7}$$

$$\begin{aligned}\tilde{w}_{\text{perm}} &= (1-\eta)\tilde{b} + \eta\left(h \times X - \beta(1-\nu)(1-\delta_{\text{perm}})\tilde{\phi}'\right) \\ &\quad + (1-\eta)\beta(1-\nu)\left\{f(\theta_{\text{perm}})(\tilde{W}'_{\text{perm}}(h) - \tilde{U}'(h))\right\}\end{aligned} \tag{A.8}$$

$$\begin{aligned}\tilde{w}_{\text{temp}} &= (1-\eta)\tilde{b} + \eta\,(A \times X) \\ &\quad + (1-\eta)\beta(1-\nu)\left\{f(\theta_{\text{temp}})(\tilde{W}'_{\text{temp}}(h) - \tilde{U}'(h))\right\}\end{aligned} \tag{A.9}$$

To derive a system of equations that are on the balanced growth, I divide all variables by X. I assume that X exhibits a steady-state rate of growth denoted by γ_X, $\gamma_X = X'/X$. Furthermore, I also assume that all exogenous variables grow at the constant rate of γ_X: $b = \tilde{b}/X$, $\phi = \tilde{\phi}/X$, and $\kappa_j = \tilde{\kappa}_j/X$. Under these assumptions, the system of equations (22)-(30) can be written as follows:

$$U(h) = b + \beta(1-\nu)\gamma_X \max \mathbb{E}\left[U_{\text{perm}}(h), U_{\text{temp}}(h)\right] \tag{A.10}$$

$$U_{\text{perm}}(h) = f(\theta_{\text{perm}})(W_{\text{perm}}(h) - U(h)) + U(h) \tag{A.11}$$

$$U_{\text{temp}}(h) = f(\theta_{\text{temp}})(W_{\text{temp}}(h) - U(h)) + U(h) \tag{A.12}$$

$$J_{\text{perm}}(h) = h - w_{\text{perm}}(h) + \beta(1-\nu)\gamma_X \mathbb{E}\left[(1-\delta_{\text{perm}})J_{\text{perm}}(h) - \delta_{\text{perm}}\phi\right] \tag{A.13}$$

$$J_{\text{temp}}(h) = A - w_{\text{temp}}(h) + \beta(1-\nu)\gamma_X \mathbb{E}\left[(1-\delta_{\text{temp}})J_{\text{perm}}(h)\right] \tag{A.14}$$

$$\kappa_{\text{perm}} = \beta(1-\nu)\gamma_X \mathbb{E}\left[q(\theta_{\text{perm}}) \int_h J_{\text{perm}}(h) d\mu^h_{\text{perm}}\right] \tag{A.15}$$

$$\kappa_{\text{temp}} = \beta(1-\nu)\gamma_X \mathbb{E}\left[q(\theta_{\text{temp}}) \int_h J_{\text{temp}}(h) d\mu^h_{\text{temp}}\right] \tag{A.16}$$

$$\begin{aligned} w_{\text{perm}} &= (1-\eta)b + \eta\left(h - \beta(1-\nu)(1-\delta_{\text{perm}})\gamma_X\phi\right) \\ &\quad + (1-\eta)\beta(1-\nu)\gamma_X\left\{f(\theta_{\text{perm}})(W_{\text{perm}}(h) - U(h))\right\} \end{aligned} \tag{A.17}$$

$$\begin{aligned} w_{\text{temp}} &= (1-\eta)b + \eta\,(A) \\ &\quad + (1-\eta)\beta(1-\nu)\gamma_X\left\{f(\theta_{\text{temp}})(W_{\text{temp}}(h) - U(h))\right\} \end{aligned} \tag{A.18}$$

Thus, the system of equations are are homogeneous of degree one in X.

A.3 Wage Determination

As explained in Section 1.5.9, a wage is negotiated between a worker and a firm according to the Nash Bargaining. The two parties split the match surplus as follows: For a new permanent worker

$$(1-\eta)(W^N_{\text{perm}} - U_{\text{perm}}) = \eta J^N_{\text{perm}} \tag{A.19}$$

For an existing permanent worker

$$(1-\eta)(W^E_{\text{perm}} - U_{\text{perm}}) = \eta(J^E_{\text{perm}} + \phi) \tag{A.20}$$

And for a temporary worker

$$(1-\eta)(W_{\text{temp}} - U_{\text{temp}}) = \eta J_{\text{temp}} \tag{A.21}$$

I derive the wage for a new permanent worker here. To derive the wage equation, I first write out the value functions in the equation A.19 using the value functions defined in sections 1.5.5, 1.5.6, and 1.5.7:

$$\begin{aligned}
(1-\eta)\Bigg(& w^N_{\text{perm}} + \beta(1-\nu)\gamma_X \Bigg\{ (1-\pi_{\text{perm}})(1-\delta_{\text{perm}}) \Big((W^E_{\text{perm}}(h,z) - U(h)) + U(h) \Big) \\
& + \pi_{\text{perm}}(1-\delta_{\text{perm}}) \Big((W^E_{\text{perm}}(h+\Delta_h, z) - U(h+\Delta_h)) + U(h+\Delta_h) \Big) \Bigg\} \\
& - b - \beta(1-\nu)\gamma_X \Bigg\{ (1-\pi_u) \Big(f(\theta_{\text{perm}})(W^N_{\text{perm}}(h,z) - U(h)) + U(h) \Big) \\
& + \pi_u \Big(f(\theta_{\text{perm}})(W^N_{\text{perm}}(h-\Delta_h, z) - U(h-\Delta_h)) + U(h-\Delta_h) \Big) \Bigg\} \Bigg) \\
= \eta \Bigg(& y^N_{\text{perm}} - w^N_{\text{perm}} \\
& + \beta(1-\nu)\gamma_X \Bigg\{ (1-\pi_{\text{perm}})((1-\delta_{\text{perm}}) J^E_{\text{perm}}(h,z) - \phi\delta_{\text{perm}}) \\
& + \pi_{\text{perm}}((1-\delta_{\text{perm}}) J^E_{\text{perm}}(h+\Delta_h, z) - \phi\delta_{\text{perm}}) \Bigg\}
\end{aligned}$$

Using the expression in equation A.20, I can simplify the expression above as follows:

$$\Rightarrow$$

$$
\begin{aligned}
& w^{N}_{\text{perm}} - (1-\eta)b - \eta(y^{N}_{\text{perm}} - Rf'(k)) \\
& \quad + \beta(1-\nu)\gamma_X \Bigg\{ (1-\pi_{\text{perm}})(1-\delta_{\text{perm}}) \Bigg(\underbrace{(1-\eta)\left(W^{E}_{\text{perm}}(h,z) - U(h)\right) - \eta J^{E}_{\text{perm}}(h,z)}_{\eta\phi} \Bigg) \\
& \quad + \pi_{\text{perm}}(1-\delta_{\text{perm}}) \Bigg(\underbrace{(1-\eta)\left(W^{E}_{\text{perm}}(h+\Delta_h,z) - U(h+\Delta_h)\right) - \eta J^{E}_{\text{perm}}(h+\Delta_h,z)}_{\eta\phi} \Bigg) \\
& \quad + (1-\eta)\Big((1-\pi_{\text{perm}})U_{\text{perm}}(h) + \pi_{\text{perm}}U_{\text{perm}}(h+\Delta_h) - (1-\pi_u)U_{\text{perm}}(h) - \pi_u U_{\text{perm}}(h-\Delta_h) \Big) \\
& \quad - (1-\pi_u)f(\theta_{\text{perm}})\eta J^{N}_{\text{perm}}(h,z) - \pi_u f(\theta_{\text{perm}})\eta J^{N}_{\text{perm}}(h-\Delta_h,z) \Bigg\} = 0
\end{aligned}
$$

Finally, the wage equation for a new permanent worker can be written as follows:

$$
\begin{aligned}
w^{N}_{\text{perm}} = {} & (1-\eta)b + \eta\left(y_{\text{perm}} - \beta(1-\nu)\gamma_X(1-\delta_{\text{perm}})\phi\right) \\
& + (1-\eta)\beta(1-\nu)\gamma_X \Big\{ (\pi_{\text{perm}} - \pi_u)U(h) + \pi_u U(h-\Delta_h) - \pi_{\text{perm}} U(h+\Delta_h) \Big\} \\
& + (1-\eta)\beta(1-\nu)\gamma_X \Big\{ (1-\pi_u)f(\theta_{\text{perm}})(W^{N}_{\text{perm}}(h) - U(h)) \\
& \qquad + \pi_u f(\theta_{\text{j}})(W^{N}_{\text{j}}(h-\Delta_h) - U(h-\Delta_h)) \Big\}
\end{aligned}
$$

One can follow the same steps to derive the wage equation for an existing permanent worker:

$$
\begin{aligned}
w^{E}_{\text{perm}} = {} & (1-\eta)b + \eta(y_{\text{perm}} + (1-\eta\beta(1-\nu)\gamma_X(1-\delta_{\text{perm}}))\eta\phi) \\
& + (1-\eta)\beta(1-\nu)\gamma_X \Big\{ (\pi_{\text{perm}} - \pi_u)U(h) + \pi_u U(h-\Delta_h) - \pi_{\text{perm}} U(h+\Delta_h) \Big\} \\
& + (1-\eta)\beta(1-\nu)\gamma_X \Big\{ (1-\pi_u)f(\theta_{\text{perm}})(W^{N}_{\text{perm}}(h) - U(h)) \\
& \qquad + \pi_u f(\theta_{\text{j}})(W^{N}_{\text{j}}(h-\Delta_h) - U(h-\Delta_h)) \Big\}
\end{aligned}
$$

Likewise, the wage equation for a temporary worker can be derived as follows:

$$\begin{aligned} w_{\text{temp}} &= (1-\eta)b + \eta(y_{\text{temp}}) \\ &\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(\pi_{\text{temp}} - \pi_u)U(h) + \pi_u U(h-\Delta_h) - \pi_{\text{temp}} U(h+\Delta_h)\Big\} \\ &\quad + (1-\eta)\beta(1-\nu)\gamma_X\Big\{(1-\pi_u) f(\theta_{\text{temp}})(W^N_{\text{temp}}(h) - U(h)) \\ &\qquad\qquad + \pi_u f(\theta_{\text{temp}})(W^N_{\text{temp}}(h-\Delta_h) - U(h-\Delta_h))\Big\} \end{aligned}$$

A.4 Computation

The computation algorithm for the model with exogenous separation is explained in this section. There is only one state variable, which is workers' skill-level, h. Because workers are heterogeneous only in their skills, workers with the same skill all search in the same market in the steady state.

The computation algorithm is explained as follows:

1. Guess, for all h, the market in which the workers with skill level h search for a job
2. Guess $U(h)$ for each skill level, h.
3. Solve for J and w using Equations 1.9, 1.10, 1.11, 1.17, 1.18, and 1.19.
4. Solve for θ and the steady-state skill distributions of workers using Equations 1.12, 1.13, and 1.20.
5. Solve for W using Equations 1.6, 1.7, and 1.8.

6. Verify that guess of $U(h)$ satisfies Equations 1.4 and 1.5 for all skill levels, h,.

   - If not, update the guess, and return to step 3. Otherwise, proceed to step 7.

7. Verify that initial guess of market that workers with skill, h, search satisfies Equation 1.3

   - If not, update the guess, and return to step 1. Repeat until convergence.

A.5 Calibration strategy for No Human Capital Accumulation Economy

Table A.1 summarizes the target moments for calibrating the model in an economy that prohibits endogenous skill accumulation. The task of the procedure is to find values of the five parameters, ϕ, b, $\bar{m}_{\text{perm}}$, $\bar{m}_{\text{temp}}$, and A in order to match five moments. The estimated parameter values are listed in Table A.2.

Table A.1: Targets and Model Moments

Moment	Data (Target)	Model Output
Job finding rate	0.155	0.1585
Ratio of job finding rate: perm/temp	0.450	0.4496
Job separation rate	0.0035	0.0033
Share of temporary worker	0.080	0.0937
Average wage ratio: perm/tem	1.681	2.2272

Table A.2: Internally calibrated parameters

Variable	Description	Value
ϕ	Firing cost	0.0375
b	Unemployment income	0.4500
$\bar{m}_{\text{perm}}$	Matching efficiency in the permanent sector	0.1461
$\bar{m}_{\text{temp}}$	Matching efficiency in the temporary sector	0.2353
A	Productivity of temporary worker	0.5335

APPENDIX B

CHAPTER 2 APPENDIX

B.1 Tables

Table B.1: Out-Of-Sample Prediction Performance (training set = 1000)

	Inflation	Output	Interest Rates	Hours	Overall
VAR(1)					
1q	0.0182	0.0078	0.0010	0.0077	-41.5178
	(0.0009)	(0.0005)	(0.0000)	(0.0001)	(0.1294)
2q	0.0182	0.0083	0.0017	0.0079	-40.5194
	(0.0008)	(0.0005)	(0.0001)	(0.0002)	(0.0731)
4q	0.0184	0.0086	0.0026	0.0080	-39.6020
	(0.0006)	(0.0004)	(0.0001)	(0.0003)	(0.0325)
8q	0.0186	0.0096	0.0034	0.0076	-39.1550
	(0.0005)	(0.0005)	(0.0001)	(0.0002)	(0.1605)
12q	0.0177	0.0096	0.0032	0.0077	-39.2795
	(0.0006)	(0.0002)	(0.0003)	(0.0001)	(0.1784)
BVAR(4)					
1q	0.0234	0.0091	0.0011	0.0085	-40.3015
	(0.0012)	(0.0008)	(0.0001)	(0.0004)	(0.2258)
2q	0.0249	0.0097	0.0018	0.0090	-39.0538
	(0.0022)	(0.0005)	(0.0001)	(0.0000)	(0.2431)
4q	0.0243	0.0107	0.0029	0.0094	-37.9293
	(0.0017)	(0.0002)	(0.0002)	(0.0001)	(0.2926)
8q	0.0239	0.0130	0.0046	0.0089	-37.1638
	(0.0009)	(0.0003)	(0.0003)	(0.0002)	(0.2680)
12q	0.0231	0.0132	0.0056	0.0091	-37.3261
	(0.0009)	(0.0004)	(0.0002)	(0.0003)	(0.0248)
RBF					
1q	0.0181	0.0079	0.0011	0.0078	-41.3677
	(0.0009)	(0.0006)	(0.0001)	(0.0001)	(0.1885)
2q	0.0182	0.0085	0.0018	0.0079	-40.4801
	(0.0009)	(0.0006)	(0.0001)	(0.0002)	(0.1386)
4q	0.0184	0.0086	0.0027	0.0080	-39.5777
	(0.0006)	(0.0005)	(0.0001)	(0.0003)	(0.0614)
8q	0.0186	0.0097	0.0034	0.0076	-39.1760
	(0.0005)	(0.0006)	(0.0001)	(0.0002)	(0.1819)
12q	0.0178	0.0095	0.0031	0.0077	-39.3235
	(0.0006)	(0.0003)	(0.0003)	(0.0001)	(0.1716)

Notes: All models are estimated using a training set whose length equals to 1000. The forecast period is 60. All models are reestimated each period. Standard errors are expressed in parenthesis. The result is based on 1000 Monte Carlo replications. The overall measure of forecast performance is the log determinant of uncentered forecast error covariance matrix.

Table B.2: Out-Of-Sample Prediction Performance (training set = 300)

	Inflation	Output	Interest Rates	Hours	Overall
VAR(1)					
1q	0.0195	0.0065	0.0009	0.0073	-42.0027
	(0.0016)	(0.0004)	(0.0001)	(0.0002)	(0.4161)
2q	0.0199	0.0065	0.0015	0.0074	-41.1171
	(0.0016)	(0.0004)	(0.0001)	(0.0001)	(0.3627)
4q	0.0197	0.0074	0.0023	0.0073	-40.2211
	(0.0009)	(0.0004)	(0.0003)	(0.0001)	(0.3805)
8q	0.0199	0.0094	0.0033	0.0074	-39.4600
	(0.0008)	(0.0009)	(0.0005)	(0.0001)	(0.3201)
12q	0.0198	0.0103	0.0040	0.0070	-39.2506
	(0.0006)	(0.0008)	(0.0004)	(0.0002)	(0.3372)
BVAR(4)					
1q	0.0259	0.0082	0.0010	0.0090	-40.2729
	(0.0004)	(0.0008)	(0.0001)	(0.0005)	(0.3259)
2q	0.0242	0.0077	0.0017	0.0093	-39.5032
	(0.0004)	(0.0004)	(0.0002)	(0.0009)	(0.2875)
4q	0.0252	0.0083	0.0025	0.0100	-38.4665
	(0.0011)	(0.0005)	(0.0002)	(0.0006)	(0.4022)
8q	0.0240	0.0095	0.0033	0.0103	-37.8527
	(0.0015)	(0.0006)	(0.0003)	(0.0006)	(0.3532)
12q	0.0257	0.0102	0.0039	0.0095	-37.6182
	(0.0018)	(0.0005)	(0.0002)	(0.0004)	(0.2969)
RBF					
1q	0.0195	0.0065	0.0010	0.0073	-41.9674
	(0.0016)	(0.0004)	(0.0001)	(0.0001)	(0.3040)
2q	0.0200	0.0064	0.0015	0.0074	-41.1195
	(0.0015)	(0.0004)	(0.0001)	(0.0001)	(0.3435)
4q	0.0197	0.0075	0.0023	0.0073	-40.2164
	(0.0009)	(0.0004)	(0.0003)	(0.0001)	(0.3655)
8q	0.0199	0.0095	0.0033	0.0073	-39.4685
	(0.0008)	(0.0010)	(0.0005)	(0.0001)	(0.3184)
12q	0.0197	0.0103	0.0039	0.0070	-39.2797
	(0.0006)	(0.0009)	(0.0004)	(0.0002)	(0.3357)

Notes: All models are estimated using a training set whose length equals to 300. The forecast period is 60. All models are reestimated each period. Standard errors are expressed in parenthesis. The result is based on 1000 Monte Carlo replications. The overall measure of forecast performance is the log determinant of uncentered forecast error covariance matrix.

Table B.3: Out-Of-Sample Prediction Performance (training set = 150)

	Inflation	Output	Interest Rates	Hours	Overall
VAR(1)					
1q	0.0200	0.0069	0.0010	0.0076	-41.5672
	(0.0027)	(0.0002)	(0.0001)	(0.0002)	(0.4227)
2q	0.0207	0.0071	0.0016	0.0077	-40.6143
	(0.0025)	(0.0005)	(0.0002)	(0.0002)	(0.5469)
4q	0.0205	0.0079	0.0026	0.0075	-39.8262
	(0.0026)	(0.0010)	(0.0004)	(0.0003)	(0.8014)
8q	0.0210	0.0102	0.0039	0.0076	-38.8626
	(0.0027)	(0.0021)	(0.0009)	(0.0003)	(0.9597)
12q	0.0210	0.0116	0.0044	0.0075	-38.6125
	(0.0032)	(0.0031)	(0.0012)	(0.0004)	(1.1208)
BVAR(4)					
1q	0.0235	0.0084	0.0011	0.0094	-40.1687
	(0.0013)	(0.0008)	(0.0001)	(0.0008)	(0.2358)
2q	0.0235	0.0089	0.0018	0.0099	-39.0100
	(0.0008)	(0.0005)	(0.0002)	(0.0005)	(0.1639)
4q	0.0256	0.0095	0.0029	0.0096	-38.0164
	(0.0017)	(0.0006)	(0.0002)	(0.0005)	(0.1994)
8q	0.0249	0.0121	0.0042	0.0105	-36.9108
	(0.0004)	(0.0007)	(0.0003)	(0.0004)	(0.3895)
12q	0.0239	0.0138	0.0055	0.0105	-36.7386
	(0.0009)	(0.0020)	(0.0006)	(0.0012)	(0.5416)
RBF					
1q	0.0203	0.0069	0.0010	0.0076	-41.5123
	(0.0024)	(0.0002)	(0.0001)	(0.0001)	(0.4225)
2q	0.0209	0.0071	0.0017	0.0077	-40.5892
	(0.0024)	(0.0006)	(0.0002)	(0.0002)	(0.5609)
4q	0.0207	0.0079	0.0026	0.0075	-39.7940
	(0.0024)	(0.0011)	(0.0004)	(0.0003)	(0.8044)
8q	0.0213	0.0102	0.0039	0.0076	-38.8302
	(0.0025)	(0.0021)	(0.0008)	(0.0003)	(0.9390)
12q	0.0216	0.0116	0.0044	0.0075	-38.5569
	(0.0028)	(0.0031)	(0.0012)	(0.0004)	(1.0927)

Notes: All models are estimated using a training set whose length equals to 150. The forecast period is 60. All models are reestimated each period. Standard errors are expressed in parenthesis. The result is based on 1000 Monte Carlo replications. The overall measure of forecast performance is the log determinant of uncentered forecast error covariance matrix.

Table B.4: Out-Of-Sample Prediction Performance (US data)

	Consumption	Investment	GDP	Hours	Inflation	Wage	FedFund	Overall
VAR(1)								
1q	0.74	1.87	0.72	0.48	0.22	0.99	0.14	-11.19
2q	1.42	4.13	1.43	1.08	0.22	1.15	0.22	-6.53
4q	2.71	9.23	3.05	2.45	0.27	1.36	0.38	-1.59
8q	4.84	17.54	5.78	4.55	0.34	2.03	0.66	3.12
12q	6.36	23.32	7.70	5.75	0.36	2.66	0.86	4.49
BVAR(4)								
1q	0.70	1.92	0.71	0.55	0.21	1.05	0.13	-11.06
2q	1.33	3.97	1.29	1.09	0.21	1.27	0.24	-6.20
4q	2.46	8.47	2.62	2.32	0.25	1.52	0.41	-1.36
8q	4.46	16.30	4.93	4.25	0.30	2.39	0.68	3.73
12q	6.26	22.31	6.90	5.45	0.31	2.98	0.88	5.80
RBF								
1q	0.78	2.69	0.86	1.12	0.25	1.01	0.19	-9.08
2q	1.38	5.02	1.48	1.59	0.27	1.18	0.33	-5.30
4q	2.33	9.18	2.59	2.41	0.31	1.46	0.54	-1.52
8q	3.89	16.01	4.47	3.83	0.35	2.17	0.76	3.76
12q	5.93	21.75	6.34	5.19	0.38	2.73	0.92	5.93

Notes: All models are estimated starting in 1955. The forecast period is 1999:1-2013:4. All models are reestimated each quarter. The overall measure of forecast performance is the log determinant of uncentered forecast error covariance matrix.

B.2 Numerical solution of nonlinear NK model

The algorithm for the numerical solution of the model is given below. There are two loops in the algorithm. The outer loop iterates over the grid, and the inner loop iterates over policy functions.

Step 0a: Solve the log-linear version of model and simulate data. This step is necessary at the very initial stage because clustering methods in Step 1 choose the grid using a sample of data points.

Step 0b: **Defining the grid and the polynomials of the RBF**. Given the simulated data, construct a grid and the associated RBF polynomials of the policy functions following [50].

Step 1: **Computing integrals**. Compute the integrals using the [50]

Step 2: **Equilibrium conditions**. Start with a guess for the model's policy functions. For each grid points, use the polynomials obtained in Step 1 to compute the values of future variables, $[\pi_{t+1}(\tilde{S}), Y_{t+1}(\tilde{S}), F_{t+1}(\tilde{S})]$. Given the future variables, solve for the endogenous state variables next period using the model's equilibrium conditions.

Step 3: **Evaluate conditional expectations**. Using the integrals computed in Step 1, evaluate the conditional expectations in equations 2.18, 2.24, 2.25.

Step 4: **Evaluate new policy functions**. Given the conditional expectations, obtain the new values of future variables in the current period, $[\pi'_t(\tilde{S}), Y'_t(\tilde{S}), F'_t(\tilde{S})]$, using equations 2.18, 2.24, 2.25. Given these new values, compute the new policy functions, and compute the difference between the polynomials of newly obtained policy functions and those of old policy functions. Denote the percentage difference as r.

Step 5: **Iteration**. If $r < 10^{-8}$, go to Step 6. Otherwise, update the guess and repeat Step 1-5.

Step 6: **Compute new grid**. Using the solution obtained in the previous steps, simulate new data. Using these simulated data, choose a new grid using [50]. Compute the difference in Euclidean norm between the old grid and the new grid. Specifically, for each newly computed grid point, find the nearest point in the old grid and compute the Euclidean distance. This forms a vector, D, that contains the distances between each new grid point to its nearest point in the old grid. Find the maximum of D and call it r_g.

Step 7: **Iteration for grid**. If r_g is smaller than the Euclidean distance between the farthest two points in the old grid, stop the algorithm. Otherwise, go back to Step 2 with the new grid obtained in Step 6.

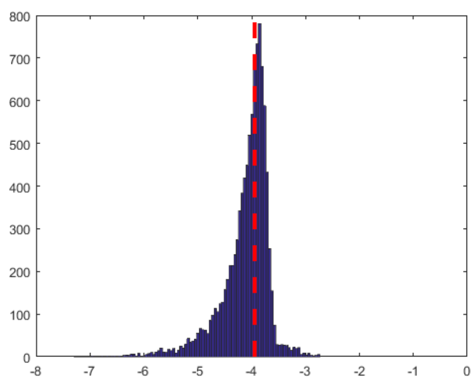
B.3 Accuracy of numerical solution

I check the accuracy of the numerical solution by computing the errors of the residual equations. Specifically, I proceed as follows. First, I simulate the model forward for 10,000 periods. This gives a simulation for both the state and control variables of the model for 10,000 periods. Second, compute the residuals from the intertemporal equations 2.18, 2.24, 2.25 for 10,000 periods. I report the decimal log of the absolute value of these residual errors.

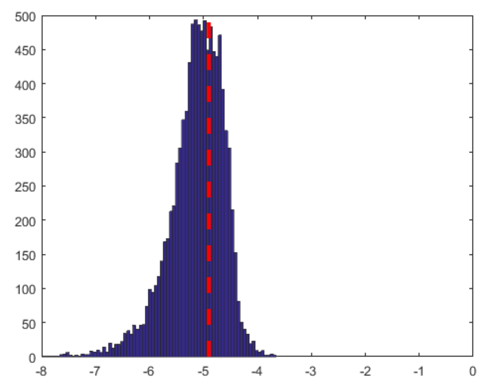
On average, residual equation errors are on order of -3.94 for equation 2.18, -4.90 for equation 2.24, and -3.44 for equation 2.25. These numbers are comparable to the other studies whose models have similar degrees of complexity.

Figure B.1: Residual equation errors

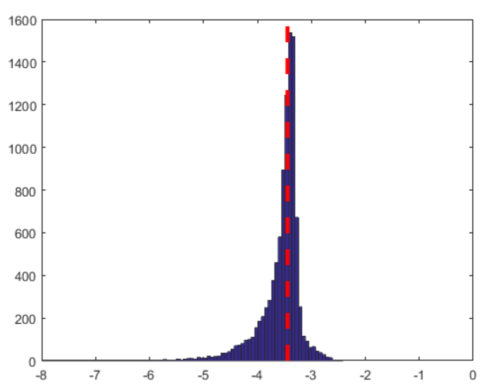
(a) Equation 2.18



(b) Equation 2.24



(c) Equation 2.25



Notes: The histograms report the residual equation errors in decimal log basis. The dotted red lines mark the mean residual equation errors.

APPENDIX C

CHAPTER 3 APPENDIX

C.1 Definition of Variables

C.2 Summary Statistics

Table C.1: Definition of Variables

Variable Name	Definition
y1cdsce	1-year maturity CDS spread observed on the day of the credit event
y1cds1y	1-year maturity CDS spread observed 1 year before the credit event
NOI	Net Open Interest: bid - ask
NOIindex	Normalized index of NOI : NOI/(bid+ask)
VIX	Volatility index of the US stock market on the day of the credit event
VIX_1y	Volatility index of the US stock market 1 year before the credit event
default year	Number of defaulted firms in a year when the auction is held
default prob. 5 year ahead	Estimated probability of default in five years (see footnote 33)
3 month labor	3-month libor observed on the day of the credit event
NCDS contract	Number of outstanding CDS contracts in the week of the credit event
NetNotional Index	Outstanding amount of net-notional values divided by gross-notional values in the week of the credit event
Zero coupon 5 year rate	"Risk-free" interest rate on the 5-year maturity US Treasury Bill on the day of the credit event
Avg. Pr. Bnds	Average price of quoted bonds on the day of the credit event
Pr. 1y Bnds	Price of 1 year residual maturity bonds on the day of the credit event
CDS region	Dummy variable, =1 if the region is associated with the reference entity
Auction Year	Dummy variable, =1 if auction is held that year
Industry	Dummy variable, =1 if the industry is associated with the reference entity

Table C.2: Summary Statistics

	obs	Mean	Std. Dev.	Variance	Skewness	Kurtosis
$\Delta S_{1,CE}$	90	-0.030	0.119	0.014	-3.875	20.667
$\Delta S_{3,CE}$	90	-0.028	0.099	0.010	-3.047	14.332
$\Delta S_{5,CE}$	90	-0.028	0.093	0.009	-2.586	11.112
NOI	156	-362.12	2212.9	489710.0	-8.224	72.027
NOIindex	142	-0.198	0.714	0.510	0.530	1.889
3 month libor	160	1.148	1.307	1.707	1.794	5.199
VIX	160	28.093	13.058	170.518	0.823	2.953
No CDS contracts (DTCC)	79	1873.2	1466.2	214976.0	1.567	5.721
NetNotional Index	79	0.083	0.037	0.001	1.545	6.442

Table C.3: Selected Correlations

	Physical sttlm req.	NOI	NOIindex	NetNotional Index	Net Notional	Gross Notional	No CDS contr (DTCC)	VIX
Physical sttlm req.	1							
NOI	-0.9976	1						
NOIindex	-0.1117	0.1319	1					
NetNotional Index	-0.1469	0.1429	-0.1781	1				
Net Notional	0.1159	-0.0859	-0.1411	0.0116	1			
Gross Notional	0.1569	-0.1309	-0.0989	-0.2826	0.8672	1		
No CDS contr (DTCC)	0.2494	-0.2305	-0.1261	-0.3032	0.8833	0.892	1	
VIX	-0.0516	0.0495	-0.2629	0.19	0.1096	0.0096	0.0411	1

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